Term structure of recession probabilities and the cross section of asset returns

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ABSTRACT

The duration of business cycles changes over time, generating time-varying investor concern about recessions. I study a new macro-factor model that directly links assets' risk premia to such concern, measured by the term structure of recession probabilities from professional forecasters. The innovation to the slope of the term structure is a negatively priced risk factor with an economically large and significant risk premium in a wide range of tests assets, consistent with how the slope predicts long-run economic activity and labor income growth. A linear factor model, including market excess return and the innovation to the slope, explains at least more than half of the cross-sectional variation of average returns on portfolios sorted on size, book-to-market, past long term return and asset growth. The factor mimicking portfolios of the model help reconcile the joint cross section of returns on equities, equity index options, and currencies and have pricing performance comparable to several multi-factor benchmarks. My evidence suggests that the slope of the term structure is a recession state variable (Cochrane, 2005), and an economic source of risk premia on test assets can be attributed to time-varying investor concern over future recessions that is priced.

***JEL classification*: E37, G12, G13, G15**

***Keywords*: Recession probability forecasts, Economic activity, Macroeconomic risks, Labor income, State variables, Value premium, Model comparison**

1 Introduction

A central ingredient of asset pricing is that the cross section of risk premia on different assets should be determined by their different exposures to *systematic risk factors*. What are the relevant systematic risk factors has long been a fundamental issue in asset pricing. In the Sharpe (1964)-Lintner (1965) Capital Asset Pricing Model (CAPM), the sole systematic risk factor is return on the aggregate wealth. A paradigm that differs from the Sharpe-Lintner static CAPM is the standard consumption-based capital asset pricing model (CCAPM) (Rubinstein, 1976; Breeden, 1979), where the systematic risk factor is aggregate consumption growth. However, there is much evidence that the static CAPM and CCAPM have limited empirical success, and they both have great difficulties in explaining the cross section of returns on equity portfolios sorted on size and book-to-market equity ratios (Breeden, Gibbons, and Litzenberger, 1989; Fama and French, 1992; Lettau and Ludvigson, 2001).

When investors face a time-varying investment opportunity set, dynamic asset pricing models, such as the Intertemporal CAPM (ICAPM) of Merton (1973), demonstrate that generally systematic risk factors are not limited to return on the aggregate wealth or aggregate consumption growth, but also consist of innovations to state variables that describe the time-varying investment opportunity set. Consequently an asset's risk premium should also be affected by its covariance with innovations to these state variables.

Arguably, macroeconomic variables can be mapped into state variables in dynamic asset pricing models as they closely link to the investment opportunity set. Empirically, macroeconomic news on economic fundamentals produce pervasive impacts on financial markets (e.g., McQueen and Roley, 1993; Flannery and Protopapadakis, 2002).[1] The idea that macroeconomic variables serve as systematic risk factors is also economically appealing because these variables provide direct linkage between risk premiums and the real economy in a rather detailed way, one goal put forward by Fama (1991), and respond to the question by Campbell (1996)—"What economic forces determine the price of risk?".

A prominent macro-factor model is the seminal work by Chen, Roll, and Ross (CRR, 1986), where exposures to innovations of five macroeconomic variables, such as industrial production and the slope of the Treasury yield curve, determine expected stock returns.

[1] Beber, Brandt, and Luisi (2015) find that the common components extracted from a large cross section of macroeconomic new flows are highly correlated with financial indicators and the stock market volatility.

Shanken and Weinstein (2006) question the CRR's findings, however. They show that the CRR's results are not robust to alternative estimation procedures of factor exposures and different test portfolios. Recently, Lewellen, Nagel, and Shanken (2010) criticize the prevailing practice of evaluating asset pricing models based on how well they explain the average excess returns on the Fama and French 25 size- and book-to-market-sorted portfolios. Strikingly, these authors show that the performance of several macro-factor models deteriorates substantially when test portfolios are expanded beyond the 25 portfolios and theoretical asset pricing restrictions are imposed ex-ante. Maio and Santa-Clara (2012) examine the time series and cross-sectional consistency of several multi-factor models in the context of the Merton's ICAPM, which prescribes that if a state variable positively forecasts market returns or market volatility, its innovation should command positive (negative) risk premium in the cross-section, and vice versa. Albeit that many multi-factor models are motivated as empirical implementations of the ICAPM, however, these authors find that only few of them meet the consistency criterion. These challenges indicate that reconciling the role of macroeconomic variables in empirical asset pricing and identifying new sources of priced macro risk factors remain important issues.

There is ample evidence that the duration of business cycles, especially recessions, varies over time (e.g., Filardo, 1994; Durland and McCurdy, 1994; Filardo and Gordon, 1998). As such, investors tend to have time-varying concern over future recessions. In this paper, I propose a new macro-factor model, where asset risk premia are directly linked to investors' perceived recession risks. Theoretically, recessions are important periods for asset pricing because they represent bad states associated with low economic activity, high unemployment rates, and high economic uncertainty, during which a typical household has above average marginal value of wealth. Assets paying more when investors' perceived recession risks increase are deemed valuable and investors are willing to accept lower returns on them, because they provide insurance against future downside consumption or labor income risks. Therefore, shocks to investors' perceived recession risk should carry negative risk premia.

In particular, a stylized fact of business cycles is that the utilization of labor is highly procyclical (Altug and Labadie, 2008). Investors may lose their jobs and become unemployed during recessions and recoveries that follow[2], and would prefer assets whose cash flows are

[2]Reinhart and Rogoff (2009) study recessions associated with major Post-World War II banking crises of developed and developing countries and find that the increase in unemployment on average lasts over four

insensitive to news of future recessions to hedge their labor income risks. When investors' labor income, or human capital, is not entirely marketable (Mayers, 1972; Campbell, 1996; Jagannathan and Wang, 1996), this specific hedging demand can have incremental impact on asset risk premia.[3] Consequently, variables that forecast future macroeconomic conditions in general, labor income in particular, are valid candidates of state variables in dynamic models. These variables are labelled as "recession state variables" by Cochrane (2005, Chapter 9). Unlike state variables in the Merton's ICAPM, recession state variables need not forecast market returns but should forecast macroeconomic activity and labor market conditions.

I measure investors' perceived recession risks by the term structure of recession probability forecasts from the Survey of Professional Forecasters (SPF), the oldest macroeconomic survey in U.S. The term structure contains probability forecasts of a decline in U.S. real gross domestic product (GDP) level in the current and subsequent four quarters, made by academic and industry researchers. These survey-based forecasts are forward-looking and model-free, distinguishing them from forecasts by statistical models based on historical data. SPF recession probabilities are fairly persistent, exhibit strong counter-cyclic dynamics, and have extra predictive power over common business cycle indicators for NBER recessions. Importantly, the SPF provides a term structure of forecasts, containing timely information on the arrivals of recessions, their durations, and the timing of recoveries that follow.[4]

Using principal component analysis, I summarize the term structure as the level and slope components. Intuitively, an above average level suggests that the economy is likely in a recession, while a heightened slope indicates an increasingly perceived probability of a recession in the near future. Using long-horizon predictive regressions, I find that the slope of the term structure significantly predicts negative macroeconomic activity and labor income growth up to 12 quarters ahead, and significantly predicts increasing stock market volatility, on top of common financial indicators, such as the term spread and default spread. This evidence is consistent with the "recession state variable" interpretation of the slope.

I estimate the risk premia for exposures to the innovations to the level and slope of the

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years, while the average duration of output contractions is much shorter, only two years.

[3]In the presence of non-marketable human capital and other non-traded assets, the aggregate stock market portfolio could be a poor proxy for the true total wealth portfolio (Roll, 1977).

[4]The latter two pieces of information would be particularly relevant when the economy is already in a recession. For instance, no one would debate on the current status of the economy when the Great Recession was on-going, but there would be substantial uncertainty about the timing of future recoveries (e.g., Reinhart and Rogoff, 2009).

term structure using cross-sectional regressions of equity portfolio returns. The innovation to the slope is negatively priced in a wide range of test portfolios, beyond the Fama-French 25 portfolios, while the innovation to the level is not robustly negatively priced. This finding on the sign of risk premia satisfies the time series and cross-sectional consistency criterion of multi-factor models advocated by Lewellen et al. (2010) and Maio and Santa-Clara (2012).

A linear factor model, including the market excess return and the innovations to the level and slope, explains more than half of the cross-sectional variation of average returns on equity portfolios sorted on firm-level characteristics such as size, book-to-market equity, long term past returns, and asset growth. Stochastic discount factor (SDF) tests (Cochrane 2005, Chapter 13) show that the innovation to the slope as a factor in the SDF helps to price equity portfolios in the presence of prominent risk factors in other models, such as the conditional CCAPM of Lettau and Ludvigson (2001) and the durable consumption CAPM of Yogo (2006). To address the critique by Lewellen et al. (2010) on evaluating asset pricing models, I include the Fama-French industry portfolios as additional test assets. I also report generalized least square (GLS) R^2s of cross-sectional regressions, as advocated by Lewellen et al., due to its appealing interpretation as a measure of a model's proximity to the mean-variance efficient frontier. In all cross sections, the innovation to the slope is negatively priced with significantly risk premiums and the proposed linear factor model delivers the highest GLS R^2s among macro-factor models considered. As a further robustness check, I conduct stock-level Fama-MacBeth cross-sectional regressions and find that the estimated risk premiums of the innovation to the slope are often highly significant, even using the thresholds of data-mining t-statistics suggested by Harvey, Liu and Zhu (2016).

In time series regressions, small and value firms have more negative exposures on the innovation to the slope of the term structure than large and growth firms, and factor exposures decrease almost monotonically in the size and book-to-market quintiles. Value (small) firms are fundamentally riskier than growth (large) firms, since the former pay poorly when investors update their beliefs that the aggregate economy likely enters into a recession. This evidence is consistent with extant findings that there are asymmetric variations of risks on small and value firms across business cycles (Perez-Quiros and Timmermann, 2000; Lettau and Ludvigson, 2001; Petkova and Zhang, 2005), lending support to the risk-based explanation of the value premium. I document similar monotonic patterns in factor exposures of equity portfolios sorted by past long term returns and asset growth, and of corporate bond portfolios sorted by credit spreads.

To shed light on the monotonic pattern of factor exposures, I run predictive regressions of future cash flow changes of book-to-marketed sorted portfolios on the level and slope. The predictive regressions for value portfolios have higher R^2s, compared to growth portfolios. Empirically, a heightened slope is associated with a larger subsequent decline in cash flows of value firms, suggesting that the monotonic pattern could be attributed to the higher sensitive of value firms' cash flows on the downside variation of cyclical risk. This finding complements former evidence that value firms are relatively distressed (Fama and French, 1993, 1995, 1996) and have higher cash flow risks than growth firms (Campbell and Vuolteenaho, 2004; Bansal, Dittmar, and Lundblad, 2005; Campbell, Polk, and Vuolteenaho, 2010).

Ideally, asset pricing models should apply to *all* asset classes, however, empirical studies often focus on some assets.[5] Lettau, Maggiori, and Weber (2014) uncover that the static CAPM, in conjunction with a downside stock market factor, can jointly reconcile cross sections of average returns on equity, equity index options, currencies, and commodity and sovereign bonds, thus providing a unified risk-based explanation for these asset classes. As a comparison, these authors show that asset-specific risk factors tailored to each asset class fail to explain the cross section of returns on other asset classes. To conduct cross-sectional tests on alternative asset classes, I create factor mimicking portfolios of the innovations to the level and slope of the term structure and incorporate equity index options and currency carry trade strategies in test assets. The factor mimicking portfolio of the innovation to the slope earns significant CAPM α and Fama-French (1993) three-factor model α of -2.4% and -1.2% per year, respectively. The factor mimicking version of the recession risk model has pricing performance comparable to the downside risk CAPM of Lettau et al. in the joint cross section of equity, equity index options, and currency returns. This evidence suggests that a possible economic force of risk premia on these assets could be attributed to investors' hedging incentives for future recession risks.

This paper relates to the empirical literature of the ICAPM, where state variables fore-

[5] Lewellen et al. (2010) suggest that test assets should be expanded beyond the size and book-to-market sorted portfolios. For instance, they suggest using bond portfolios. Notable recent exceptions along this line include Constantinides, Jackwerth, and Savov (2013), Adrian, Etula, and Muir (2014), Lettau, Maggiori, and Weber (2014), and Koijen, Lustig, and Nieuwerburgh (2015), among others. Indeed, an important agenda for empirical asset pricing research is to reconcile stochastic discount factors across different asset classes, as put forward by Cochrane in his American Finance Association presidential address (Cochrane, 2011).

cast the investment opportunity set. A partial list of papers includes Campbell (1996), Chen (2002), Brennan, Wang, and Xia (2004), Campbell and Vuolteenaho (2004), Hahn and Lee (2006), Petkova (2006), Maio and Santa-Clara (2012), Maio (2013), and Boons (2016). State variables in these papers, such as the default spread, are derived from financial markets and are most often motivated by their ability to predict future market returns.[6] In contrast, state variables here are motivated by their ability to predict long-run macroeconomic conditions and are directly derived from investor beliefs over future recessions. Additionally, the macro factor proposed satisfies the time series and cross-sectional consistency and is robust to the Lewellen et al.'s critique. The contribution of this paper is to directly highlight the importance of time-varying investor concern over future recessions, as a recession state variable, for the cross section of expected asset returns, and suggest that an economic source of risk premia on test assets might be attributed to investors' hedging incentives for future recessions. Manski (2004) points out the advantage of studying expectation data directly instead of inferring preferences and expectations from observed choices, because the latter can yield results consistent with various alternatives, while the former approach helps relax restricted assumptions about expectations and sharpens identification.

The paper also relates to the literature on the joint cross section of multiple asset classes by showing that exposures to investors' perceived recession risk help reconcile the cross section of expected returns on currencies and equity index options. Constantinides, Jackwerth, and Savov (2013) show that the CAPM with one of several crisis-related equity factors explains the cross section of stock and equity index option returns. Adrian, Etula, and Muir (2014) propose a risk factor based on broker-dealer leverage ratios, and find that this single factor well explains the cross section of average returns on Treasury bonds, and equity portfolios sorted on size, book-to-market equity, and past returns. Koijen, Lustig, and Nieuwerburgh (2015) show that a three-factor model, including market excess return, the level of the yield curve, and the Cochrane-Piazzesi factor, can explain the cross section of returns on stocks, Treasury bonds, and corporate bonds better than the Fama-French three-factor model. My paper differs in the economic source of risk factors and the scope of test assets. First, the recession probabilities are model-free measurements of recession risks, directly derived from investors' beliefs. Empirically, the term structure is shown to contain

[6] One notable exception is Boons (2016) who uses the term spread and the default spread variables as state variables and motivates them by their ability to forecast long-run macroeconomic activity.

extra information about macroeconomic activity and labor income beyond that in the yield curve. Second, I demonstrate that the recession risk factor model helps reconcile the cross section of returns on equity index options and currencies, in addition to equity returns.

Finally, my empirical analyses are based on the term structure of SPF recession probabilities, which contains timely information about future recessions and recoveries at different maturities. van Binsbergen, Hueskes, Koijen, and Vrugt (2013) show that the cyclical components of aggregate dividends, GDP, and consumptions are correlated, especially during recessions. Consequently, similar information also exists in dividend market derivatives. These authors show that the term structure of equity yields, with the expected dividend growth as one of their components, has superior predictive ability for future consumption growth over nominal and real bond yields during the past decade. Moreover, a dividend market product, called dividend steepener, has been used by macro traders to bet on the exact timing of a recession and the recovery that follows (van Binsbergen, Brandt, and Koijen, 2012). Therefore, these dividend derivatives provide higher frequency, market-based, and longer maturity complements to the SPF forecasts.

The rest of the paper proceeds as follows. Section 2 describes the data of SPF recession probabilities and explores its information content. Section 3 presents long-horizon predictive regressions, showing that the slope of the term structure strongly predicts future macroeconomic activity, labor income growth, and stock market volatility. Section 4 presents the theoretical prediction on the pricing of perceived recession risk, empirical methodology, and cross-sectional asset pricing tests for different asset classes. The last section concludes.

2 Data

This section describes the term structure of recession probability forecasts and explore its information content in forecasting future recessions dated by the NBER.

SPF Recession probabilities

The measures of investors' perceived recession risks are recession probability forecasts from the SPF database, one of the oldest macroeconomic surveys in the United States. The SPF summarizes macroeconomic forecasts from leading financial institutions, professional forecasting firms and academic institutions. Historically, it was conducted by the American Statistical Association in conjunction with the NBER. After the second quarter of 1990, the Federal Reserve Bank of Philadelphia took it over. The SPF forecasts are probabilities of a decline in U.S. real GDP in the current quarter and subsequent four quarters.[7]

Formally, a quarter-t forecast of the recession probability in quarter-$t+i$ is defined as,

$$Rec_{t,i} \equiv Pr_t(GDP_{t+i} < GDP_{t+i-1}) = Pr_t(\triangle GDP_{t+i} < 0), i \in \{0, 1, ..., 4\} \quad (1)$$

where time t is measured in quarters and GDP_{t+i} refers to the level of real GDP in quarter-$t+i$. Note that the data consist of $Rec_{t,0}$, the current quarter recession probability. This is because the survey is released to the public in the mid-month of each quarter, much in advance of the announcement day of the actual current quarter GDP. Because there are many individual forecasters in the cross section, in what follows, I take the cross-sectional average of individual forecasts as my proxy for perceived recession probabilities.

Before proceeding, I introduce a set of macroeconomic quantities and prices that are closely related to business cycles. Definitions of these variables and data sources are in Appendix A. The first four macro variables are seasonally adjusted quarterly growth rates of key macroeconomic quantities. Specifically, $\triangle \boldsymbol{IP}$ denotes the growth rate of the industrial production index. $\triangle \boldsymbol{c}$ refers to the growth rate of real per capita consumption. $\triangle \boldsymbol{GDP}$ and $\triangle \boldsymbol{l}$ are the growth rates of final revised real GDP in billions of chained 2009 dollars, and real per capita labor income, respectively. The quarter-t growth rates of these variables are formed as the natural log difference of their levels between quarter-t and quarter $t-1$.

The remaining four macro variables are derived from asset prices, including the term spread (**TERM**), the default spread (**DEF**), the log dividend-price ratio on the value-weighted index of all NYSE/AMEX/NASDAQ stocks from the Center for Research in Security Prices (CRSP) ($\boldsymbol{d/p}$), and the excess return on the CRSP value-weighted index (**Mkt**).

[7]Prior to 1992Q1, the forecasting target was real GNP. For the release dates of vintage data, see `https://www.philadelphiafed.org/-/media/research-and-data/real-time-center/survey-of-professional-forecasters/spf-release-dates.txt?la=en`. On average there are 38 individual forecasters in the cross section. The one quarter ahead recession probability forecast was named "The Anxious Index" by New York Times journalist David Leonhardt and has been used in asset pricing by David and Veronesi (2013). In addition to recession probabilities, SPF contains forecasts on levels and growth rates of key macroeconomic quantities and prices, such as CPI and unemployment rates. See Croushore (1993) for the detailed description. Several macroeconomic forecasts in SPF have been examined in the literature. For instance, SPF inflation forecasts are shown to be superior to both term structure models and leading financial indicators in forecasting future inflations (Ang, Bekaert, and Wei, 2007).

In the asset pricing literature, the first three have long been viewed as business cycle indicators that predict the financial investment opportunity set. There is also much evidence that they track and predict future economic activity and risk premia of stocks and bonds (e.g., Chen, Roll and Ross, 1986; Keim and Stambaugh, 1986; Campbell, 1987; Fama and French, 1988, 1989; Harvey, 1988, 1989; Chen, 1991; Estrella and Hardouvelis, 1991; Estrella, 2005).

Figure 1 plots the series of recession probabilities. The shaded areas are NBER recessions. Each recession probability is time-varying and exhibits strong counter-cyclic dynamics. Table I report summary statistics of the recession probabilities and macroeconomic variables. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters in total.

[**Insert Table I here**]

Panel A reports the sample moments. The mean of recession probabilities ranges from 17.2% (Rec_3) to 19.24% (Rec_1). The mean is always higher than the median and the gap between the two is largest for the current quarter forecast Rec_0, indicating that Rec_0 experienced more upward spikes. Notably, the median of the recession probabilities, robust to outliers, increases monotonically from 9.7% (Rec_0) to 16.74% (Rec_4). Thus, the average term structure is upward sloping. Panel B shows correlations between the recession probabilities and macro variables. As expected, all recession probabilities are negatively correlated with the growth rates of GDP, consumption, and labor income, and positively associated with the default spread and the dividend-price ratio. Another interesting feature is that a higher recession probability is associated with a downward sloping yield curve, measured by the term spread, and the magnitude of the correlation is increasing in the forecasting horizon.

Predicting NBER recessions

To investigate the information content of SPF recession probabilities, I examine their ability to predict NBER recessions. I estimate a probit model of the dummy variable D_{t+i}, $i \in \{0, 1, 2, 3\}$, taking the value of 1 if quarter $t + i$ is in an NBER recession, 0 otherwise. The probit model is specified as follows,

$$D_{t+i} = \begin{cases} 1, \text{quarter } t+i \text{ is in an NBER recession} \\ 0, \text{otherwise} \end{cases} \tag{2}$$

$$Pr(D_{t+i} = 1|\mathcal{F}_t) = \Phi(\beta_0 + \beta_1 Rec_{t,i} + \beta_2 Rec_{t,i+1} + \gamma X_t) \tag{3}$$

where $Pr(D_{t+i} = 1|\mathcal{F}_t)$ is the probability that quarter-$t+i$ is in an NBER recession conditional on quarter-t information set $\mathcal{F}_t$, Φ is the cumulative distribution function of a standard normal variable, $Rec_{t,i}$ and $Rec_{t,i+1}$ are the key predictors, and X_t is quarter-t control variables. Following Estrella and Mishkin (1998), X_t consists of the term spread (TERM) and the excess return on the value-weighted CRSP index (Mkt).[8]

Table II reports maximum likelihood estimates of the probit model. The left panel shows the specifications excluding the control X_t. From each forecast horizon i, $Rec_{t,i}$ enters into the model with a significantly positive coefficient, that is, higher values of $Rec_{t,i}$ are uniformly associated with higher likelihoods of future NBER recessions. The forecast for the next quarter $Rec_{t,i+1}$ does not provide additional information. The economic impact of $Rec_{t,i}$ is sizable. The average marginal effects of $Rec_{t,i}$ range from 0.4% to 1.47%. The Hosmer-Lemeshow goodness-of-fit test does not reject any model at the 5% significance level, suggesting that the probit models fit the sample well. As probit models are nonlinear, the R^2 of ordinary least square (OLS) regressions does not apply. Estrella and Mishkin (1998) develop a pseudo R^2 of the probit model, which takes values between 0 ("no fit") and 1 ("perfect fit") and shares a similar interpretation as OLS R^2s. The pseudo R^2s for predicting D_t and D_{t+1} are 0.53 and 0.33, respectively, indicating that the recession probabilities of the current and the next quarter do reasonably well in forecasting NBER recessions.

The right panel of the table reports estimates for the full specification. Though including leading financial variables improves the model fitting substantially, the significance and magnitudes of the coefficients on $Rec_{t,i}$ barely change. The only exception is that $Rec_{t,3}$ is subsumed by the term spread. Overall, SPF recession probabilities are strong predictors

[8] Estrella and Mishkin (1998) investigate the predictive power of various macro variables and financial variables in forecasting NBER recessions. They conclude that the term spread and stock market return are the most powerful leading financial indicators. However, the zero lower bound problem emerged in recent decades dampens the predictive power of the term spread as the lower bound prevents the long term yield from dropping below 0 to yield a downward sloping yield curve (e.g., Ergungor, 2016). To make the estimated coefficients comparable, both the term spread and the CRSP index return are in percentage terms.

for NBER recessions and they contain incremental information beyond that in the yield curve and the stock market return. In unreported analyses, I also find that the recession probabilities significantly predict the events of negative real GDP growth.

[**Insert Table II here**]

Principal components of recession probabilities

The correlation matrix in Table I (B) suggests that the SPF recession probabilities do not co-move with each other perfectly over time. To separate pieces of information in the term structure and summarize its dynamics concisely, a natural way is to use principal component analysis to decompose the term structure. Figure 2(A) shows the loadings of the first two principal components on each recession probability.[9] The loadings of the first component (hereafter $PC1$) are all positive, despite that $PC1$ has higher weights on $Rec_{t,0}$ and $Rec_{t,1}$. The second component (hereafter $PC2$) captures the slope of the term structure, as $PC2$ loads positively on probabilities for remote quarters and negatively on probabilities for nearby quarters. Thus $PC1$ and $PC2$ can be roughly interpreted as the "level" and "slope" of the term structure. Figure 2(B) shows that $PC1$ and $PC2$ account for around 88% and 10% of the variation of the term structure, respectively. Taken together, $PC1$ and $PC2$ account for 98% of the total variation, therefore the dynamics of the term structure is largely summarized by its level and slope, which will be my focus in the subsequent analyses.

[**Insert Table III here**]

Table III reports summary statistics of $PC1$ and $PC2$. Panel A presents their moments over the full sample and over NBER recessions, respectively. $PC1$ has a sample mean of 32.79 and is highly volatile, with a standard deviation of 28.94. The persistence of $PC1$ is fairly high, with a first-order autocorrelation coefficient of 0.8. The mean of $PC2$ is 15.41, consistent with the average upward sloping term structure, and $PC2$ is less volatile than $PC1$. Comparing the moments across business cycles, the mean of $PC1$ is much higher in recessions than in expansions, and the differences in mean across business cycles is highly significant ($t = -9.66$). The mean of $PC2$ is lower in recessions than in expansions,

[9] I drop $Rec_{t,4}$ in subsequent empirical analyses because it has four missing observations in the early sample period.

indicating that the term structure is on average downward sloping during recessions, although the difference in mean is not significant ($t = -1.46$).

Figure 3 plots the dynamics of $PC1$ and $PC2$. $PC1$ is highly counter-cyclical, as it always peaks in recessions and declines substantially in expansions. In contrast, $PC2$ behaves very differently from $PC1$. It rises quickly during several quarters immediately prior to NBER recessions, while heads downward and even becomes negative in the late stage of recessions. In particular, $PC2$ attained its minimum of -10.9 in the last quarter of the early 1970s recession. This pattern suggests that there is a lead-lag relation between $PC1$ and $PC2$, which is confirmed in Panel C.

The first four columns of Panel B show the contemporaneous correlations between principal components and the macro variables. $PC1$ has positive correlations with d/p ($\rho = 0.39$) and DEF ($\rho = 0.57$), and weak negative correlation with TERM ($\rho = -0.15$). This result indicates that $PC1$ tracks valuations of equities and low-grade corporate bonds. As $PC1$ is fairly persistent, this evidence is consistent with the intuition that when perceived future economic conditions are persistently poor, valuations of risky assets decline. $PC2$ has a negative correlations with TERM ($\rho = -0.41$) and a positive correlation with d/p ($\rho = 0.14$), but does not correlate with DEF.

Fama and French (1989) find that after 1951, TERM tracked cyclic fluctuations of the aggregate economy at the usual NBER business cycle frequency. Chen (1991) studies the relation between a set of business cycle indicators and real GNP growth. He finds that DEF and d/p have negative and significant correlations with past growth rates of real GNP, but they predict future real GNP growth up to two quarters ahead. In contrast, TERM does not correlate with past real GNP growth, however, it positively predicts future GNP growth up to five quarters ahead. Estrella and Mishkin (1998) conclude that TERM is one of the most powerful leading financial indicators of NBER recessions. Hence it seems that $PC1$ and $PC2$ carry different information about future economic activity. The conjecture is that $PC1$, mainly correlated with DEF and d/p, summarizes past and current business conditions, while $PC2$, mainly correlated with TERM, contains forward-looking information about future economic activity. Section 3.1 provides supporting evidence of this hypothesis.

The rest columns in Panel B report contemporaneous correlations of $PC1$ and $PC2$ with changes in the macroeconomic conditions, including the quarterly excess return on the CRSP value-weighted index (Mkt), and quarterly growth rates of industrial production ($\triangle IP$), real per capita consumption ($\triangle c$), real GDP ($\triangle GDP$), and real per capita labor income ($\triangle l$). Notably, $PC1$ has economically large and statistically significant negative correlations with the growth rates of $\triangle IP$ ($\rho = -0.67$), $\triangle c$ ($\rho = -0.52$), $\triangle GDP$ ($\rho = -0.62$), and $\triangle l$ ($\rho = -0.38$), while $PC2$ has virtually no correlations with these variables. This result also suggests that $PC1$ and $PC2$ contain different information, and highlights the ability of $PC1$ to track current business conditions. Panel C examines the lead-lag relation between $PC1$ and $PC2$ via a first-order vector autoregression (VAR(1)). The "slope" of the term structure, $PC2$, predicts the future "level", $PC1$, but not vice versa. A one-unit change in the slope translates into an almost one-unit change in the future level of the term structure.

3 Information content of the term structure

Recessions are periods with low real economic activity and heightened economic uncertainty (Bloom, 2014). Given that $PC1$ (level) and $PC2$ (slope) summarize most of the time variations of the term structure of recession probabilities, they should forecast real macroeconomic activity and economic uncertainty. In addition, investors may suffer adverse and undiversifiable labor income shocks in recessions as they may lose their jobs or small business, therefore $PC1$ and $PC2$ should also forecast future labor income growth. To test these hypotheses, I run (in-sample) long-horizon predictive regressions of future growth rates of key macroeconomic quantities on $PC1$ and $PC2$. My goal is not to stress that $PC1$ and $PC2$ are the best predictors via horse-race comparisons, but rather to demonstrate that they have the incremental information beyond that in common business cycle indicators.

3.1 Predicting macroeconomic activity and labor income

Following the literature, I measure real economic activity by the growth rates of the industrial production index, real GDP, and real per capita consumption (Fama, 1990; Estrella and Hardouvelis, 1991), and compute the growth rate of real per capita labor income in a way similar to Jagannathan and Wang (1996). Because both dependent and independent variables are available quarterly, the sample is quarterly from 1968Q4 to 2015Q1. The specification of the predictive regressions is as follows,

$$y_{t\to t+h} = \alpha(h) + b1(h)PC1_t + b2(h)PC2_t + \theta(h)X_t + \epsilon_{t,h} \tag{4}$$

where $y_{t\to t+h} \equiv 400/h\ (\log y_{t+h} - \log y_t)$ is the annualized continuously compounded growth rate of y_t from quarter t to quarter $t+h$. The forecasting horizon h takes values of 1, 4, 8, 12 and 16, that is, 1 quarter to 4 years ahead.

The macro control variable X_t includes the term spread, the default spread, the short-term nominal interest rate proxied by the three-month T-bill rate ($y^{(3m)}$), the log dividend-price ratio of the CRSP value-weighted index, and the CRSP value-weighted excess return, all of which are included for their superior ability to forecast real economic activity and labor income (Harvey, 1988, 1989; Fama, 1990; Chen, 1991; Estrella and Hardouvelis, 1991; Campbell, 1996; Ang, Piazzesi, and Wei, 2006; Gilchrist and Zakrajšek, 2012, among others). For instance, Harvey (1988) shows that in the framework of the CCAPM, the slope of the real term structure of interest rate is linearly related to expected real consumption growth. Empirically, he finds that the real term spread predicts ex-post real consumption growth up to three quarters ahead. Estrella and Hardouvelis (1991) also document that the term spread predicts the growth rates of real GNP and all its private sector components at horizons of more than two years ahead, and that it outperforms a large set of forward-looking indicators.[10] Finally, X_t also consists of the past one-period growth rate $y_{t-1\to t}$ because in Table I, the growth rates of consumption, GDP, and industrial production exhibit non-negligible first-order autocorrelations.

Table IV reports OLS estimates of the predictive regressions. In the baseline specification (first column within each block), the control X_t is excluded, while the extended specification (second column) includes X_t. t-statistics of $b(h)$ are adjusted as in Newey and West (1987) with two lags for the one-quarter horizon ($h = 1$), and as in Hodrick (1992) for longer horizon predictive regressions with overlapping observations.

[10] Chen (1991) finds that in univariate regressions, the default spread and dividend-price ratio predict real GNP growth up to two quarters ahead, while the term spread and three-month T-bill rate forecast the growth rate up to four quarters ahead. Ang, Piazzesi, and Wei (2006) model the joint dynamics of the yield curve and real GDP growth as a VAR; their calibration suggests that the term spread, and in particular the short-term nominal rate, must be included together for forecasting future GDP growth. Indeed, there is a long tradition that utilizes the information in the yield curve to predict future macroeconomic activity. See Cochrane and Piazzesi (2005), Koijen, Lustig, and Nieuwerburgh (2015), and the references therein.

[**Insert Table IV here**]

Notably, $PC1$ and $PC2$ correctly forecast the future direction of real economic activity, either independently or jointly with X_t, as the coefficients of $PC1$ and $PC2$ are almost uniformly negative. Starting with the baseline specification, most of the coefficients of $PC2$ are significantly negative, and their (absolute) magnitudes and associated t-statistics decay very slowly across the horizons. Indeed, at 16 quarters ahead, $PC2$ remains a significant predictor for the first three growth rates at 5% level. In contrast, the coefficients of $PC1$ decline rapidly, lose statistical significance beyond the horizon of eight quarters ahead, and even turn into positive at 16 quarters ahead. Consequently, the economic impact of $PC2$ is much larger than that of $PC1$. For instance, at eight quarters ahead, a one standard deviation increase of $PC2$ (9.56) is on average associated with -1.33%, -0.35%, -0.63%, and -0.63% decline in the annual growth rates of industrial production, real per capita consumption, real GDP, and real per capita labor income, respectively, ceteris paribus. The corresponding effects of $PC1$ are -0.38%, -0.14%, -0.26%, and -0.17%, respectively. These pieces of evidence support the conjecture in Section 2 that compared with $PC1$, $PC2$ mainly contains information about future long-run macroeconomic conditions.

The preceding conclusions barely change when the control X_t is included. For brevity, coefficients of X_t are omitted. The default spread plays a minor role, while the CRSP excess return, and especially the term spread and the short-term interest rate strongly predict macroeconomic activity at all horizons, consistent with the literature. The term spread reduces the significance of $PC2$ for industrial production growth and real GDP growth at the horizon of four quarters ahead, but does not affect its predictive power at longer horizons. Importantly, the power of $PC2$ is extended to the three years ahead even in the presence of the leading business cycle indicators, and only becomes weak at four year ahead. Furthermore, the in-sample $\bar{R}^2s$ are large, suggesting that the variations of the predictable components of real economic activity, consumption growth, and labor income growth are substantial at the usual business cycle frequency. Specifically, $\bar{R}^2$s for the real GDP growth range from 29% ($h = 1$) to 36% ($h = 16$). These magnitudes are consistent with Estrella and Hardouvelis (1991). Similar $\bar{R}^2s$ in predictive regressions of industrial production growth by past aggregate stock market returns are documented by Fama (1990).

3.2 Predicting stock market volatility

I then test the ability of $PC1$ and $PC2$ to predict economic uncertainty, proxied by expected stock market volatility. The following analyses center on the predictive regressions of the Chicago Board Options Exchange (CBOE) VIX index and long term VIX indices. The squared CBOE VIX index is a model-free estimate of the expected quadratic variation of S&P 500 Index returns over the subsequent 30 days under the risk-neutral measure. The squared long term VIX indices, from Johnson (2015), are model-free estimates of the expected quadratic variations of the S&P 500 Index returns over subsequent 3, 6, and 12 months.[11] In representative-agent equilibrium models, for instance Drechsler and Yaron (2011), the time variation in perceived economic uncertainty is the most important driver of VIX indices. This motivates me to proxy expected economic uncertainty by VIX indices. Empirically, Bloom (2009) demonstrates that a former version of the CBOE VIX index is highly correlated with various measures of economic uncertainty at the both firm- and macro-levels.

The quarterly predictive regressions are specified as follows,

$$\log VIX_{\tau,t+h} = \alpha(\tau,h) + b1(\tau,h)PC1_t + b2(\tau,h)PC2_t + \theta(\tau,h)X_t + \epsilon_{\tau,t+h} \tag{5}$$

where t is measured in quarters, h is one quarter, $\log VIX_{\tau,t+h}$ is the logarithm of a quarter-$t+h$ VIX index with maturity τ, and X_t includes quarter-t control variables. Since VIX indices are strictly positive and exhibit large positive skewness, the logarithm transformation renders regression errors close to normal distributions. The samples of the CBOE VIX index and long term VIX indices run from January 1990 to April 2015 and January 1996 to August 2013, respectively. Table V reports OLS estimates of the predictive regressions.

[**Insert Table V here**]

The baseline specification include the term spread, default spread, and time-t monthly log return on the S&P 500 Index for the leverage effect (Black, 1976) as controls. In the second specification, X_t further contains the one-period lagged dependent variable, as all VIX indices are highly persistent with first-order autocorrelation coefficients in excess of

[11] See Johnson (2015) for details on the VIX data. I thank Travis L. Johnson for making the VIX term structure data available `http://faculty.mccombs.utexas.edu/johnson/data.html`. Technically, VIX indices contain two components, the conditional expected quadratic variations of the S&P 500 Index returns under the physical measure, and a risk premium component. In this paper, I do not differentiate the two.

0.8. In both specifications, $PC1$ is subsumed by the default spread. By contrast, $PC2$'s coefficients are positively significant and economically large, even after controlling for lagged VIX indices. Thus, $PC2$ contains incremental information on future expected stock market volatility beyond the information in common business cycle indicators. The sample means of the logarithm VIX indices are close to 3 for all maturities. In the first (second) specification, a one standard deviation increase in $PC2$ (9.56) is associated with a 7.3% (3.5%) percentage increase in the three-month VIX index when it is at the sample mean.

To conclude, this section shows that the slope of the term structure, $PC2$, negatively forecasts future macroeconomic activity as well as labor income, and positively forecasts future expected stock market volatility at all horizons. $PC1$, the level of the term structure, negatively forecasts short- and medium-term macroeconomic activity and labor income. The findings imply that positive shocks to $PC1$ and especially to $PC2$ are bad systematic news to investors that will increase their marginal utility of wealth.

4 Pricing of perceived recession risk

This section studies the asset pricing implication of the innovations to the level and slope of the term structure of recession probabilities. I discuss the theoretical motivation of the sign of risk premia on these innovations and present cross-sectional asset pricing tests.

4.1 Theoretical prediction

I motivate the sign restriction between the time series and cross section in the context of intertemporal asset pricing models. In the Merton's ICAPM, innovations to state variables that positively forecast future market returns command positive risk premia in the cross section, since exposures to this type of state variable risks cannot help investors hedge the risk of changing investment opportunities and better smooth their consumption streams.

As Cochrane (2005, Chapter 9) points out, however, an important assumption of the Merton's ICAPM is that all sources of wealth, including human capital, are fully marketable. As a result, the only state variables are those that forecast future market returns. In reality, investors own assets that are not fully marketable, such as human capital (Mayers, 1972; Campbell, 1996; Jagannathan and Wang, 1996, among other). They may lose their jobs or small business in recessions, and hence prefer assets whose payoffs are less sensitive to news of future economic downturns to hedge their labor income risk. In equilibrium, this special hedging demand for labor income risk can affect expected asset returns. For instance, in a discrete-time ICAPM in which total wealth comprises stock market wealth and non-marketable human capital, Campbell (1996) demonstrates that innovations to variables that can forecast future stock market returns or labor income are valid risk factors in the cross section. Therefore, variables that forecast future likelihood of recessions in general, labor income in particular, are valid candidates of state variables. State variables of this sort are named as "recession state variables" by Cochrane (2005, Chapter 9).

The preceding evidence collectively shows that an increase in the level ($PC1$), and e-specially in the slope ($PC2$) of the term structure is associated with subsequent periods with lower macroeconomic activity, heightened stock market volatility, and lower real labor income growth. Thus, shocks to $PC1$ and $PC2$ represent systematic news to macroeconomic activity and labor market conditions. In this regards, $PC1$ and especially $PC2$ are likely to be "recession state variables" of special hedging concern to investors. In the cross section, assets paying more when there are positive shocks to the level or slope of the term structure are deemed valuable, and investors are willing to accept lower returns on them because they provide insurance against future downside labor income risks. This implies that the innovations to $PC1$ and $PC2$ should be priced with negative market prices of risk.[12]

4.2 Empirical methodology

I examine the theoretical prediction on the sign of risk premia in the cross section of stock returns using the two-pass cross-sectional regression (CSR) approach developed by Black, Jensen, and Scholes (1972) and Fama and MacBeth (1973). While the theoretical argument pins down the sign of risk premia, the empirical analyses quantify the magnitudes of the

[12]An alternative explanation based on the long-run risks model of Bansal and Yaron (2004) yields similar implications. Positive shocks to $PC1$ or $PC2$ are bad news for future aggregate consumption and will raise the current marginal value of wealth of the representative agent if she prefers resolving intertemporal consumption risks sooner—the agent prefers early resolution of uncertainty (Epstein and Zin, 1989). Assets whose payoffs positively covary with shocks to $PC1$ or $PC2$ are deemed valuable because they provide insurance against unfavorable shifts in macroeconomic conditions, or more directly, because their payoffs positively covary with the agent's marginal utility. Consequently, investors are willing to accept lower returns on these assets so that shocks to $PC1$ and $PC2$ are negatively priced. Compared with $PC1$, $PC2$ predicts long-run macroeconomic activity as well as economic uncertainty, and hence, quantitatively, the shock to $PC2$ might be more important in asset pricing than the shock to $PC1$.

risk premiums and answer two additional questions. First, do the innovations to $PC1$ and $PC2$ carry negative risk premia in the cross section of asset returns that are statistically and economically significant? Second, do the innovations to $PC1$ and $PC2$ as risk factors help reconcile the cross-sectional variations of risk premiums on different asset classes?

To proceed, I quantify the innovations to $PC1$ and $PC2$ by a first-order vector autoregression VAR(1),

$$Z_{t+1} = A_0 + A_1 Z_t + u_{t+1} \tag{6}$$

where $Z_t \equiv (PC1_t, PC2_t)'$. The residuals u_{t+1}, denoted as $(\triangle PC1_{t+1}, \triangle PC2_{t+1})'$ for convenience, are the innovations to $PC1$ and $PC2$ extracted by the VAR. The estimates of VAR are reported in Panel C of Table III. The correlation between $\triangle PC1$ and $\triangle PC2$ is -0.11 and is not significantly different from 0. In the ICAPM literature, VARs are widely used to extract innovations to state variables (Campbell, 1996; Campbell and Vuolteenaho, 2004; Petkova, 2006).[13] Also, the first-order autocorrelations of $PC1$ and $PC2$ are 0.8 and 0.6 in Table III, respectively; therefore, extracting innovations via VARs avoids the over-difference problem. Figure 4 plots the estimated innovations to $PC1$ and $PC2$ by the VAR and also the first difference method. The two types of innovations co-move over time with a time series correlation exceeding 0.8. As is evident from the figure, however, the first difference approach tends to overstate the magnitudes of innovations after large movements.

I estimate the risk premia for exposures to the innovations to $PC1$ and $PC2$ using unconditional two-pass CSRs of equity portfolio returns, conditional on the realized innovations estimated via the VAR. I test a three-factor recession risk model, where the first factor is market excess return, proxied by excess return on the CRSP value-weighted index (Mkt), and the rest are the innovations to $PC1$ and $PC2$ extracted via the VAR. The unconditional CSR involves two stages. The first stage entails the estimation of full sample factor exposures (βs) of each asset via a time series regression of its excess returns on the three risk factors.[14] In the second stage, factors' risk premia are estimated by a single CSR of average

[13] My VAR specification is slightly different, as I do not include market excess return in the VAR. This is because both PCs, especially $PC2$, have little correlations with the market as shown in Table III.

[14] There are three ways of estimating factor exposures in the first stage, including rolling-window, extending-window, and full sample regressions, all of which are widely used in the literature. See Black, Jensen, and Scholes (1972), Fama and French (1992), Lettau and Ludvigson (2001), and Petkova (2006), among others. I adopt the full sample regression because it connects the unconditional two-pass CSRs to the stochastic discount factor representation of linear factor models, and it can be readily estimated by Generalized Method of Moments.

excess returns of test assets on their factor exposures.

Specifically, let $R^e_{i,t}$ denote excess return on asset i over the period $[t-1,t]$. The time series regression of $R^e_{i,t}$ over the full sample yields its unconditional factor exposures β^i_{Mkt}, $\beta^i_{\triangle PC1}$, and $\beta^i_{\triangle PC2}$, respectively.

$$R^e_{i,t} = a_i + \beta^i_{Mkt} Mkt_t + \beta^i_{\triangle PC1} \triangle PC1_t + \beta^i_{\triangle PC2} \triangle PC2_t + \epsilon^i_t, \ i = 1, ..., N \tag{7}$$

Next, a single CSR of average excess returns of all sets on their unconditional factor exposures yields estimated market prices of risk associated with the three factors,

$$E_T[R^e_{i,t}] = \alpha + \beta_{i,Mkt}\lambda_{Mkt} + \beta_{i,\triangle PC1}\lambda_{\triangle PC1} + \beta_{i,\triangle PC2}\lambda_{\triangle PC2} + \xi_i, \ i = 1, ..., N \tag{8}$$

where $E_T[R^e_{i,t}]$ denotes the time series average of excess returns on asset i, α refers to the excess zero-beta rate, and ξ_i is the model pricing error of asset i.

The key asset pricing restrictions on cross-sectional regressions are that estimated factors' risk premia should be consistent with theory (ICAPM) and are economically and statistically significant in the cross section of different test assets (Lewellen, Nagel, and Shanken, 2010; Maio and Santa-Clara, 2012; Adrian, Etula, and Muir, 2014). Further, both the excess zero-beta rate and pricing errors should be insignificantly. Following the literature, I report several diagnostic statistics for CSRs, including the mean absolute pricing error (MAPE, $\frac{1}{N}\sum_{i=1}^{N}|\xi_i|$), adjusted cross-sectional $\bar{R}^2$ (Jagannathan and Wang, 1996) that gauge how well model-implied expected excess returns explain the cross-sectional variation of average excess returns, and a χ^2 statistic that formally tests whether pricing errors $\{\xi_i\}_{i=1}^N$ are jointly zero. To compute the statistic, I translate two-pass CSRs into a set of moment conditions, estimated by a one-stage Generalized Method of Moments (GMM), where the weighting matrix is specified in a way such that the GMM yields OLS estimates of both first and second stage regressions. The χ^2 statistic is the Hansen (1982)'s over-identification J_T statistic of these moment conditions (Cochrane, 2005, Chapter 12).

Because βs in second-stage CSRs are generated regressors, rendering OLS t-statistics biased (Shanken, 1992), I report robust t-statistics (t-GMM) based on the one-stage GMM, that correct the errors-in-variables problem for βs and that adjust for heteroscedasticity and autocorrelation as in Newey and West (1987) with one lag. Fama-MacBeth t-statistics

(t-FM) adjusted by Newey and West standard errors are also reported.

4.3 Main results

Cross-sectional analysis

I estimate the recession risk model (7-8) using the Fama-French 25 size and book-to-market (B/M) sorted portfolios in conjunction with the CRSP value-weighted index.[15] The sample is quarterly from 1969Q1 to 2014Q4 (184 quarters). Monthly returns on test portfolios are compounded into quarterly returns, and quarterly excess returns are formed as returns in excess of the return on the one-month T-bill. Table VI summarizes the cross-sectional results where the estimated risk premia are reported as percentage per quarter.

[**Insert Table VI here**]

Specification I shows the performance of the CAPM. Although there is substantial cross sectional variation of average returns, all test assets have similar market βs (Fama and French, 1992, 2006).[16] As a result, market βs explain only 4% of the cross-sectional variation and the J_T statistic of 86.05 strongly rejects the CAPM. In specification II, the market price of risk for the innovation to the level of the term structure $\triangle PC1$ is large and negative, -6.2% per quarter, consistent with the prediction in Section 4.1, but is insignificant. $\triangle PC1$ as an additional factor to the market does not improve the fit, as the cross-sectional $\bar{R}^2$ only slightly increases from 4% to 8%. Specification III and the full model specification IV show that the innovation to the slope of the term structure $\triangle PC2$ is negatively priced with robust t-statistics of 2.19 (2.28), consistent with how the slope predicts long-run macroeconomic activity and labor income. The magnitude of its risk premium is also large, -4.99% (-7.47%) per quarter in specification III (IV).[17] Furthermore, $\triangle PC2$ as an additional risk

[15]Monthly returns on the 25 portfolios and one-month T-bill are from Kenneth French's web site, `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french`. I thank Kenneth French for making the portfolio data available.

[16]Thus, there is a multicollinearity problem induced by the intercept, i.e., the excess zero-beta rate, and the market βs (Jagannathan and Wang, 2007). Consequently, the excess zero-beta rate is significantly positive, while the estimated market risk premium is negative.

[17]The first-stage time series regressions that follow show that the factor exposures of $\triangle PC1$ and $\triangle PC2$ are smaller than those of market factor, leading to large estimated market prices of risk. Inflated risk premiums of non-traded factors are commonly observed in the literature, because embedded "noises" in macro factors that are unrelated to asset returns tend to generate downward biases of estimated factor exposures, and consequently boost estimated market prices of risk (Adrian, Etula, and Muir, 2014).

factor substantially improves the cross-sectional fit as the $\bar{R}^2$s increase to 57% and 64% in specification III and IV, which are comparable to the $\bar{R}^2$ of the Fama-French three-factor (1993) model (62%). J_T statistic fails to reject the full model specification at the 5% level. Thus, statistically the three-factor recession risk model captures the cross-sectional variation of average excess returns on the 25 portfolios.

Figure 5 plots the sample average excess returns on the test assets against their expected excess returns implied by each model. I label each 25 size and book-to-market sorted portfolios using a two-digit number where the first (second) digit denotes the size (book-to-market) quintile. If a model fits the cross section perfectly, all points should fall on the 45-degree line. The figure echoes the results of cross-sectional $\bar{R}^2$s. In the top left panel, there are large deviations between CAPM-implied expected returns and actual average returns. In contrast, in the bottom left panel, the plot for the recession risk model is much closer to the 45-degree line. The only exception is the "puzzling" low average excess return on the small-growth portfolio (labelled 11), which has been a well known challenge, even for the Fama-French three-factor model (bottom right panel).

Hahn and Lee (2006) show that three risk factors, including changes in the default spread ($\triangle DEF$), changes in the term spread ($\triangle TERM$) and market excess return, capture most of the cross-sectional variation of average returns on the 25 portfolios and argue that the size and book-to-market effects are compensation for risks related to time variations in credit market conditions and in the yield curve. Since $PC2$ has a significantly negative correlation with $TERM$ ($\rho = -0.41$), it is possible that $\triangle PC2$ is priced because $PC2$ is correlated with the term spread, a positive priced state variable. However, the two slopes are conceptually different. Despite the fact that the term spread is a strong predictor for future recessions and real economic activity, it is also affected by Fed's monetary policy and other issues such as the zero lower bound constraint (Estrella, 2005; Hahn and Lee, 2006; Ergungor, 2016), while the slope of the term structure of recession probabilities is a measure derived from pure forecast of future recession risk. Empirically, I examine whether $\triangle PC2$ is still priced in the presence of $\triangle TERM$ and $\triangle DEF$. Specification V shows that $\triangle PC2$ remains a negatively priced factor with an estimated risk premium of -4.69%, the magnitude of which is similar to that in specification III. Thus, $\triangle TERM$ and $\triangle DEF$ do not subsume $\triangle PC2$. Subsection *Model Comparison*, which follows, revisits this issue in more detail.

A key restriction on CSRs, discussed in Section 4.2, is that estimated factors' risk premia should be consistent with theory and are significant in the cross section of different test assets. Cross-sectional tests for an asset pricing model, however, often hinge on the choices of test portfolios (Lewellen, Nagel, and Shanken, 2010; Kan, Robotti, and Shanken, 2013, among others). Therefore, I conduct further CSRs using various equity and bond portfolios to examine whether $\triangle PC2$ remains negatively priced and helps explain the cross-sectional variation of risk premia on different assets.[18] The results are reported in Table VII.

[**Insert Table VII here**]

Panel A of in Table VII reports results using the 25 size- and book-to-market-sorted portfolios with 6 Fama Treasury bond portfolios sorted by maturity, and 5 corporate bond portfolios sorted by credit spreads. Bonds with higher credit spreads are riskier and have higher default risks. Presumably, issuers of these bonds tend to be relatively distressed. Nozawa (2012) shows that the credit spread is a key bond-level characteristic that strongly predicts future bond excess returns, and there is sizable positive average return spread between portfolios of bonds with high and low credit spreads.

The test assets in Panel B are 25 portfolios double-sorted by size and past long-term returns (past 60 month to 13 month cumulative returns). Fama and French (1996) show that past long-term losers behave as small distressed firms and have higher exposures on their Small-Minus-Big (SMB) and High-Minus-Low (HML) factors than do past winners. As such, past long-term losers (winners) tend to be value (growth) stocks and the average return spread between past long-term winners and losers, similar to that between value and growth stocks, can also be attributed to the distress premium (Fama and French, 1996).

Panel C reports results for 25 portfolios double-sorted by size and investment—measured by growth rate of book value of total assets.[19] Cooper, Gulen, and Schill (2008) and Fama and

[18]In particular, one caveat in Table VI is that the estimated risk premium of $\triangle PC1$ is significantly positive in the full model specification. On the surface, this could be partially attributed to the negative correlation between $\triangle PC1$ and $\triangle PC2$. More generally, this finding tends to change with test portfolios. To address this issue, I conduct CSRs on various test portfolios, and also run stock-level cross-sectional regressions. More often, the risk premium on $\triangle PC1$ is negative but insignificant.

[19]The Fama bond portfolios are from CRSP, which comprise U.S. T-bills or T-Notes with maturities of 0-1, 1-2, 2-3, 3-4, 4-5, and 5-10 years, respectively. The corporate bond portfolios are from Lettau, Maggiori, and Weber (2014). Nozawa (2012) constructs 10 corporate bond portfolios sorted by credit spread. Lettau, Maggiori, and Weber (2014) equally weigh these portfolios into 5 portfolios. The data in Panel B and C are from Kenneth French's web site. The 25 size and long-term-reversal (investment) sorted portfolios are constructed through the intersection of five portfolios sorted by market equity and five portfolios sorted by cumulative return over the prior 60 months to 13 months (percentage changes in firms' total assets).

French (2008) show that asset growth is a strong firm-level characteristics that negatively predict future stock returns, especially for small- and medium-cap stocks. Anderson and Garcia-Feijóo (2006) find that the book-to-market equity ratio is empirically related to past capital investment growth. Growth (value) firms tend to accelerate (decelerate) investment two to three years prior to the portfolio formation period. Xing (2008) interprets the value and investment effects in a standard Q-theory with a stochastic discount factor. Under certain conditions, high book-to-market stocks are firms with lower marginal Q, implying that all else being equal, they face higher discount rates and hence make less investment and earn higher future returns. In sum, credit spreads, past long-term returns, and asset growth are characteristics closely linked to book-to-market ratios at firm-level. The following empirical analysis investigates whether the recession risk model provides a coherent story for the three cross sections.

Not surprisingly, the CAPM cannot explain these cross sections of anomaly returns. However, in Panel A, when bond portfolios are included, the multicollinearity problem induced by the unit vector and market βs is mitigated, and the market has a positive risk premium. In specification II, the estimated risk premium of $\triangle PC1$ is negative across all cross sections, albeit only significant at 10% level in Panel A. $\triangle PC1$ as an additional risk factor to the market only slightly improves the CAPM. Turning to specification III and the full model specification, $\triangle PC2$ is negative priced with significant and sizable risk premia varying from -3.84% to -6.95%. The cross-sectional $\bar{R}^2$s of specification III and the full model are dramatically improved, with a lower bound of 48%. Thus, the factor exposures to $\triangle PC2$ account for at least half of the cross-sectional variation of average returns on these assets.[20]

Collectively, the evidence shows that $\triangle PC2$ is negatively priced in various equity and bond portfolios, consistent with the theoretical prediction. Value stocks, past long term losers, low capital investment stocks, and high credit spread corporate bonds have more negative exposures on the innovations to the slope $\triangle PC2$. These assets are fundamentally risky in that they all have larger exposures to systematic news about future downside business cycle risks and deliver lower returns when there are positive shocks to perceived recession

[20]The specification of the three-factor recession risk model is motivated by the "recession state variable" hypothesis of $PC1$ and $PC2$ in the context of the ICAPM. As a robustness check, I test a two-factor specification using the same portfolios in which market excess return is excluded. $\triangle PC2$ remains negatively priced, while $\triangle PC1$ is not significantly priced. However, compared to the full model specification, the cross-sectional $\bar{R}^2$s of the two-factor specification are lower, ranging from 24% (Panel C) to 65% (Panel A).

probabilities. Furthermore, exposures to $\triangle PC2$ play a key role in reconciling the cross-sectional variation of risk premia on these test assets.

Lewellen, Nagel, and Shanken's critique

Lewellen, Nagel, and Shanken (2010) criticize the practice of evaluating asset pricing models solely based on how well they explain the cross sectional variation of average returns on the Fama-French 25 size- and book-to-market-sorted portfolios. The authors emphasize that the 25 portfolios exhibit a strong factor structure, since almost all the time variation of their returns and the cross-sectional variation of their average returns can be captured by the Fama-French three factors. As such, finding a high cross-sectional OLS R^2 and significant factor risk premia of a linear factor model is not striking, and is actually a low hurdle. Following Prescription 1 in Lewellen et al. (2010), the test assets are expanded to include the 30 Fama-French industry portfolios to reduce the strong factor structure. I also report GLS R^2s of CSRs (hereafter R^2_{GLS}, Prescription 3 in Lewellen et al.). Unlike OLS CSRs, GLS regressions are invariant to the portfolio repackaging, and hence the strong factor structure problem is less severe. Also, from an investment prospective, GLS R^2 is more economically appealing because it measures a model's proximity to the true mean-variance efficient frontier.[21]

As a comparison, I consider several macroeconomic factor models in Lewellen et al. (2010): i) the conditional consumption-CAPM (CC-CAY) by Lettau and Ludvigson (2001), in which the consumption-wealth ratio CAY is the conditioning variable; ii) the linearized version of the durable consumption-CAPM (D-CCAPM) by Yogo (2006), where the factors are the market return, the growth rates of durable and nondurable consumption, $\triangle c_{dur}$ and $\triangle c$; iii) the linearized version of the ultimate consumption risk model (U-CCAPM) of Parker and Julliard (2005), where the sole risk factor is the cumulative growth rate of nondurable consumption over the current and subsequent 11 quarters; and iv) the intertemporal CAPM specification of Hahn and Lee (2006) (HL).[22] In addition, I report results of the CAPM, the

[21]OLS CSRs are not independent of repackaging of portfolios. Roll and Ross (1994) and Kandel and Stambaugh (1995) show that the R^2 of an OLS regression of average returns on the betas of an inefficient market proxy can be an arbitrary value between 0 and 1. Thus the value of the OLS R^2 provides no guidance on the location of the inefficient market proxy in the mean-standard deviation space.

[22]These models are chosen because they are representative macro-factor models that explain the cross-sectional variation of average returns on the 25 size- and B/M-sorted portfolios quite well. CC-CAY and D-CCAPM are also studies in Lewellen et al. (2010).

Fama-French three-factor model, and the CCAPM. Table VIII summarizes the results. The sample is quarterly from 1969Q1 to 2014Q3, restricted by data availability.

[**Insert Table VIII here**]

The estimated risk premium of $\triangle PC2$ is -7.52% per quarter ($t = -2.27$) using the 25 portfolios and drops to -2.99% ($t = -1.99$) in the large cross section with industry portfolios. A lower risk premium in the larger cross section is not entirely surprising as there is not much cross-sectional variation in the average industry portfolio returns. Nevertheless, $\triangle PC2$ remains negatively priced. Turning to the diagnostic statistics, when the test assets are the 25 portfolios, the recession risk model delivers both the highest OLS $\bar{R}^2$ (64%) and GLS R^2_{GLS} (15%) among all models. When the test assets also include the industry portfolios, the recession risk model outperforms all macro-factor models with higher OLS $\bar{R}^2$ (19%) and R^2_{GLS} (5%), which are only exceeded by the $\bar{R}^2$ (28%) and R^2_{GLS} (7%) of the Fama-French three-factor model. This evidence confirms that $\triangle PC2$ is robustly priced with a negative risk premium, and lends further support for the theoretical prediction in Section 4.1.

Model comparison

The preceding analyses show that the recession risk model outperforms several macro-factor models with higher cross-sectional OLS and GLS R^2s. While R^2 is an intuitive goodness-of-fit measure to rank pricing models' performance, the difference in it does not tell us statistically how much a model outperforms another.[23] In this section, I employ two formal approaches to rigorously compare different models, from asset pricing perspectives.

The first approach is a GMM test based on the Stochastic Discount Factor (SDF) representation of linear factor models (Cochrane 2005, Chapter 13.4). The GMM SDF test examines whether one set of risk factors drives out another in the SDF; that is, in the presence of the former, one can ignore the latter for pricing asset returns. Recall that a CSR of average excess returns on βs is based on the expected excess return-beta representation: $E[R^e] = \beta_f \lambda_f$, where $E[R^e]$ denotes a vector of expected excess returns, and β_f and λ_f are the unconditional factor exposures and market prices of risk for the linear factor f, respectively. It is well known that there is an equivalent relation between the beta representation

[23]Lewellen, Nagel, and Shanken (2010) first propose to obtain the distribution of sample cross-sectional R^2s via Monte Carlo simulation. Kan, Robotti, and Shanken (2013) further develop the asymptotic distributions of sample R^2s as well as model comparison tests based on sample R^2s of different models.

and linear SDFs (Ross, 1978; Dybvig and Ingersoll, 1982). In particular, when the test assets are excess returns, the mean of the SDF cannot be identified. A common practice is to specify a normalized linear SDF: $M = 1 - b'[f - \mu_f]$, where $\mu_f = E[f]$. Consequently, the fundamental asset pricing equation $E[MR^e] = 0$ readily implies the beta representation of expected excess returns,

$$E[R^e] = E[R^e(f-\mu_f)']b = Cov(R^e, f)b = \beta_f \underbrace{Var(f)b}_{\lambda_f} \quad (9)$$

Suppose f can be decomposed into two sets of non-overlapping risk factors f_1 and f_2, i.e., $f \equiv [f_1', f_2']'$, where f_i has K_i factors, $i = 1, 2$. Denote $M = 1 - b_1'(f_1 - \mu_{f_1}) - b_2'(f_2 - \mu_{f_2})$. The GMM SDF test that examines if f_2 is driven out by f_1 simply tests $b_2 = 0$, and the associated Wald statistic $\hat{b}_2'\hat{Var}(\hat{b}_2)^{-1}\hat{b}_2$ follows an asymptotic $\chi^2_{K_2}$ distribution.[24] To calculate the statistic, I form the following two sets of moment conditions, taking into account the fact that the means of risk factors are estimated.

$$g(b, \mu_f) \equiv \; E\begin{bmatrix} (1 - b_1'(f_1 - \mu_{f,1}) - b_2'(f_2 - \mu_{f,2}))R^e \\ f - \mu_f \end{bmatrix} = 0 \quad (10)$$

The SDF parameters (b, μ_f) are estimated by the Hansen (1982)'s efficient GMM.[25] Given that there are many prominent models, the first test asks whether in the presence of risk factors from these models, the coefficient of $\triangle PC2$ in the SDF is zero. This is the very test suggested by Cochrane. Alternatively, I report Wald statistics for the opposite hypothesis that coefficients of (non-overlapping) factors from other models are zero in the SDF, given

[24] The correct test for the hypothesis is $b_2 = 0$ rather than $\lambda_{f_2} = 0$, where λ_{f_2} is f_2's risk premium. The two will be equivalent when $Var(f)$ is a diagonal matrix. A similar test for the hypothesis is developed by Kan, Robotti, and Shanken (2013) in the context of two-pass cross-sectional regressions.

[25] The efficient GMM has two stages. The first-stage GMM sets $A\ g(b, \mu_f) = 0$, where A is given by

$$A \equiv \begin{bmatrix} Cov(f, R^e) & 0 \\ 0 & I_{K_1+K_2} \end{bmatrix}$$

The second stage GMM sets $d'S^{-1}g(b, \mu_f) = 0$, where $d \equiv \frac{\partial g}{\partial [b'\ \mu_f']}$ and S is the spectral density matrix of moment conditions. I obtain the time series of moment conditions by plugging in the first-stage GMM estimates and estimate S as in Newey-West via the Bartlett kernel with a window length of 1.

I also employ an alternative two-stage GMM, where the first stage is identical to that in the efficient GMM, but the second stage sets $\tilde{A}\ g(b, \mu_f) = 0$. $\tilde{A}$ is A, except that $Cov(f, R^e)$ is replaced by $Cov(f, R^e)S_{11}^{-1}$, where S_{11} is the spectral density matrix of the first set of moment conditions, estimated in the same way as above. This method is equivalent to the GLS cross-sectional regression. The results barely change except that the coefficient of $\triangle PC_2$ is not significant in the presence of the Fama-French three factors.

the presence of the three factors in the recession risk model (7-8). I consider the same set of linear factor models in the preceding analyses except for the CAPM, which is nested by the recession risk model, and the test assets are the same 56 portfolios.

Panel A of Table IX summarizes the results. The first block presents the Wald χ^2_1 statistics for the hypothesis that $\triangle PC2$ is driven out by risk factors in the six models, separately. The χ^2_1 statistics reject the hypothesis at the 5% significance level for all the models; therefore given other models' risk factors, $\triangle PC2$ still helps price test portfolios. Among the six models, the χ^2_1 statistic of the CCAPM is the least significant, because of the large variation of pricing errors. In untabulated results, the hypothesis that both $\triangle PC1$ and $\triangle PC2$ are driven out is also rejected at the 5% level for all models. The second block of Panel A shows the reverse tests. Among the six models, I cannot reject the hypothesis that factors in the CCAPM or in the U-CCAPM can be dropped in the presence of the three factors in the recession risk model. These findings are not entirely striking since $PC1$ is negatively correlated with contemporaneous consumption growth and $PC2$ predicts consumption growth up to 12 quarters ahead. To conclude, there is strong evidence that $\triangle PC2$, as an additional risk factor, helps price excess returns on the size, book-to-market, and industry sorted portfolios in the presence of existing macro factors.

[**Insert Table IX here**]

Turning to the second approach, I compare different models by the Hansen-Jagannathan (HJ) distance. Hansen and Jagannathan (1997) develop this model mis-specification measure, representing the minimal distance (in the mean-squared metric sense) between a candidate SDF and the set of all admissible SDFs that can price test assets exactly. The HJ distance is proportional to the absolute pricing error of the most mis-priced portfolio among portfolios with the unit second moment. Therefore, the measure is invariant to the repackaging of portfolios. These appealing interpretations makes the HJ distance an economic metric that can universally gauge the absolute performance of any asset pricing models.

Panel B of Table IX reports the squared sample HJ distances, denoted as δ^2, for the six models and the recession risk model, as well as their differences, denoted as $\delta^2_{model} - \delta^2_{rec}$. The p-values for the hypothesis $\delta^2 = 0$ are reported, using the Lagrange multiplier test in Gospodinov, Kan, and Robotti (2013, Theorem 1). The test portfolios in the first (second) block are gross returns on the 25 size- and B/M-sorted portfolios and the CRSP value-weighted index (the 25 portfolios, the 30 industry portfolios, and the CRSP index). Consistent with the findings on OLS and GLS $\bar{R}^2$s, the recession risk model has the lowest squared HJ distance of 0.375 among all models when the test assets are the 26 portfolios, while it has a lower HJ distance (0.920) than all macro-factor models in the cross-section of 56 portfolios and is outperformed only by the Fama-French three-factor models (0.897). Thus, empirically the recession risk model is closer to the set of admissible SDFs, compared with other macro-factor models. As evident from the p-values, however, all these models are mis-specified in terms of HJ distances.

To gauge the statistical significance of $\delta^2_{model} - \delta^2_{rec}$, I adopt the test strategy in Gospodinov, Kan, and Robotti (2013), who develop a general econometric framework with a series of tests to compare nested or non-nested pricing models based on sample HJ distances. Also see the paper by Kan and Robotti (2009). However, the evidence is inconclusive for the given sample. Although the recession risk model has lower squared sample HJ distances than other macro-factor models, the series of tests cannot reject that these squared HJ distances are equal at the conventional significance level. Similar to the conclusion in Kan and Robotti (2009), due the modest sample size on quarterly data, the returns and risk factors considered seem too noisy to distinguish one model from another based on their HJ distances.

Time series analysis

Preceding results show that $\triangle PC2$ is a robustly priced factor with a negative risk premium, and the recession risk model captures the cross-sectional variation of average excess returns on the 25 size- and B/M-sorted portfolios. These findings together imply that portfolios with higher average returns, such as portfolios with small stocks and value stocks, must have more negative exposures on $\triangle PC2$. The subsequent analyses focus on the first-stage time series regressions and offer possible explanations for the patterns in factor exposures.

Table X summarizes the average excess returns and the time series regressions (7) on the 25 size- and B/M-sorted portfolio returns. Panel A shows that the average quarterly excess returns on the 25 portfolios exhibit pronounced size and B/M effects, consistent with the literature.

Panel E (F) reports factor exposures of the 25 portfolios on $\triangle PC1$ ($\triangle PC2$). Small (Big) and high (low) B/M stocks have negative (positive) factor exposures on $\triangle PC1$, $\beta_{\triangle PC1}$s.

However, $\beta_{\triangle PC1}$s across either size or B/M quintile do not vary in a monotonic fashion. In contrast, in line with the size and B/M effects, for each book-to-market quintile, $\beta_{\triangle PC2}$ declines as the firm size decreases, and for each size quintile, $\beta_{\triangle PC2}$ falls as the book-to-market ratio rises. Put differently, comparing with growth (large) stocks, value (small) stocks earn more negative returns when there are positive shocks to the slope of the term structure of recession probabilities. Section 3.1 shows that a heightened slope is associated with subsequent periods with lower real aggregate output and labor income. Thus, value (small) stocks pay less when investors update their beliefs that the aggregate economy will more likely enter into a recession in the near future. Notably, $\triangle PC2$ as a priced risk factor is derived from macroeconomic forecasts on business cycles, and hence is less likely correlated with stock-level mispricing. This evidence lends support to the risk-based explanation for the value premium and complements existing evidence that there are counter-cyclical variations of risk levels in small and value stocks across business cycles (Perez-Quiros and Timmermann, 2000; Lettau and Ludvigson, 2001; Petkova and Zhang, 2005).

[**Insert Table X here**]

Both $\triangle PC1$ and $\triangle PC2$ are non-traded factors. One concern is that they are useless factors in the sense that they have very weak correlations with asset returns (Kan and Zhang, 1999). Panel F (H) reports robust t-statistics of estimated factor exposures on $\triangle PC1$ and $\triangle PC2$. 12 out of 25 absolute values of t-statistics for $\beta_{\triangle PC2}$ exceed 2. A likelihood-ratio test of the hypothesis that $\beta_{\triangle PC1}$s ($\beta_{\triangle PC2}$s) are jointly zero yields a χ^2_{25} statistic of 80.57 (74.46), which strongly rejects the useless factor hypothesis.

I then investigate the potential explanation of the monotonicity of $\beta_{\triangle PC2}$ across book-to-market quantile. Previous studies document that value stocks are relatively distressed (Fama and French, 1993, 1995, 1996) and have higher cash flow risks than growth stocks (Campbell and Vuolteenaho, 2004; Bansal, Dittmar, and Lundblad, 2005; Campbell, Polk, and Vuolteenaho, 2010, among others).[26] These extant findings, in conjunction with the finding that $PC2$ is a strong predictor of future long-run macroeconomic activity, suggests

[26] Using the return decomposition approach, Campbell and Vuolteenaho (2004) find that returns on value stocks have higher exposures on news about future aggregate cash flows than do growth stocks. Bansal et al. (2005) show that the dividend growth of value stocks is more sensitive to innovations to smoothed aggregate long-run consumption growth. Campbell et al. (2010) directly show that the cash flows of value stocks are more sensitive to shocks to aggregate cash flows.

that the cross-sectional difference in $\beta_{\triangle PC2}$s may be attributed to the higher sensitivity of the cash flows of value stocks to the time variation of investor concern over future recessions.

To examine this conjecture, I measure a firm's cash flows by its profitability (return on total assets (ROA)), defined as the current year operating income before depreciation divided by the average total assets of the current and preceding years. I form five B/M-sorted portfolios using all CRSP common stocks, following Fama and French (1992). The portfolio-level profitability is the value-weighted ROA of individual firms. I then run the following predictive regressions of changes in the portfolio-level profitability on $PC1$ and $PC2$. If the conjecture is true, the coefficients of $PC2$ should be negative, and the magnitudes should decrease in the B/M quintile. Since accounting data is available at the annual frequency, the sample is annually from 1969 to 2013, 45 years in total. The predictive regression is as follows,

$$\overline{\triangle \text{Profit}}^{i}_{t-1\to t+h-1} = \alpha^i(h) + b1^i(h)PC1_t + b2^i(h)PC2_t + \epsilon^i_{t,h} \tag{11}$$

where time t is measured annually, $\overline{\triangle \text{Profit}}^{i}_{t-1\to t+h-1} \equiv \frac{100}{h}(\text{Profit}^i_{t+h-1} - \text{Profit}^i_{t-1})$ is the annualized cumulative change in the profitability of portfolio i from year $t-1$ to year $t+h-1$ (in percent), and the forecasting horizon h takes values of 2, 3, and 4.[27] Since the absolute values of first-order autocorrelation of the one-period profitability changes $\triangle\text{Profit}_{t-1\to t}$ across all portfolios are less than 0.15, the mean-reversion of $\triangle\text{Profit}_{t-1\to t}$ is not a major concern; hence, I exclude lagged profitability in the regressions.

Table XI presents the results. $PC1$'s coefficients are negative across all horizons, but do not decrease monotonically in the B/M quintile. Besides, their magnitudes and associated t-statistics are rather small for the high book-to-market quintile. The coefficients of $PC2$ are also uniformly negative, and are more negative for the high B/M quintile. Thus, the future change in profitability of value stocks is more sensitive to fluctuations in the slope of the term structure, which contains information on long-horizon macroeconomic activity. These findings are consistent with the conjecture.

[**Insert Table XI here**]

Specifically, $PC2$'s coefficients decrease monotonically from -0.011 for the low B/M quin-

[27] Following the convention in the literature, I assume that accounting information for year-$t-1$ is available at the end of June at year-t. Thus, I use $PC1$ and $PC2$ at the end of June at year-t to predict annualized cumulative changes in profitability from year-$t-1$ to year-$t+h-1$, where $h \in \{2, 3, 4\}$.

tile to -0.021 for the high B/M quintile when the forecasting horizon h is 2 and from -0.017 to -0.029 when h is 3, though the statistical significance of the difference in $PC2$'s coefficients across the B/M quintile cannot be established. On average, a one standard deviation increase in $PC2$ is associated with 0.11%, 0.14% and 0.21% decline in the annualized profitability for the low, median, and high B/M quintile over two years, $\overline{\triangle\text{Profit}}_{t-1\to t+1}$. To understand the economic significance, note that the sample means of the one-year profitability change $\triangle\text{Profit}_{t-1\to t}$ are -0.39%, -0.20% and -0.31% for the low, median, and high B/M quintile, respectively; therefore the effect of a one standard deviation increase in $PC2$ on $\overline{\triangle\text{Profit}}_{t-1\to t+1}$ is sizable, ranging from 15% to 35% of its sample mean, respectively.

Notably, $\bar{R}^2$s for the high book-to-market portfolio are at least two times higher than those for the low book-to-market portfolio and the magnitudes peak at two year. Thus, the predictable variation, using recession probability forecasts as predictors, is much larger for value stocks than for growth stocks. This is direct evidence that the cash flow of value stocks are more exposed to (downside) cyclical variations of business cycle risks.

Stock-level analysis

Estimated factor exposures of individual securities are noisy, and suffer error-in-variable problems. Thus, empirical asset pricing tests often group individual securities into portfolios. However, some authors advocates the use of individual securities as test assets, for the efficiency gain in the cross-sectional regressions (e.g., Litzenberger and Ramaswamy, 1979; Ang, Liu, and Schwarz, 2011). Given the large number of individual securities, there is a wide dispersion in average returns and factor exposures, which dramatically increases estimation efficiency and precision of factors's risk premia. Importantly, using individual securities as test assets not only increases the statistical power, but also helps alleviate the "spurious inference" problem caused by using characteristics-sorted portfolios that are known to exhibit a strong factor structure (Daniel and Titman, 1997, 2012; Kan and Zhang, 1999; Lewellen, Nagel, and Shanken, 2010).

Table XII reports the results of Fama-MacBeth (hereafter, FM) cross-sectional regressions of quarterly stock excess returns on historical factor exposures on market, $\triangle PC1$, $\triangle PC2$, and a set of firm-level characteristics. The test assets are individual common stocks from the CRSP. Quarter-t factor exposures are estimated by rolling regressions of excess returns on market, $\triangle PC1$, and $\triangle PC2$ with a 20-quarter window prior to quarter-t, requiring at least 16 quarter return observations in a given window. Firm-level characteristics include size and book-to-market equity ratios, past 12 month to 2 month cumulative returns, gross profitability, and asset growth, to control for the size, value, momentum, profitability, and investment effects.[28] Because of the initial five year window for factor exposure estimation, the sample is quarterly from 1974Q1 to 2014Q12. Financial firms with the first SIC digit of 6 and firms that have less than 2 year of observations in Compustat are excluded. I impose the constraint that the excess zero-beta rate is zero.

[**Insert Table XII here**]

In Panel A, test assets are all stocks in the CRSP. By imposing the zero excess-beta constraint, the aforementioned multicollinearity problem is reduced, and market is positively priced across all specifications. In specification I, $\triangle PC1$ is negatively priced with a sizable quarterly risk premium of -1.9% per quarter, the sign of which is consistent with the theoretical prediction. However, $\triangle PC1$ is driven out by firm characteristics in the remaining specifications. By contrast, $PC2$ is robustly priced in the cross section of individual stock returns, even after controlling for all the five characteristics. Including gross profitability and asset growth reduces the magnitude and significance of its risk premium, but do not drive it out. 4 out of 5 Fama-MacBeth t-statistics of factor exposures on $\triangle PC2$, adjusted by Newey-West standard errors, exceed 3, the threshold of data-mining-adjusted t-statistics (Harvey, Liu, and Zhu, 2016).[29] Interestingly, once the zero excess-beta constraint is imposed, the coefficient of log(ME) is positive, a slightly opposite size effect in my sample period. In addition, the momentum effect is also quite weak in the sample.

As a robustness check, Panel B performs same cross-sectional regressions, but test assets are only stocks listed in New York Stock Exchange (NYSE). The average firm size in NYSE, 4.1 billions, is much larger than the average of 2 billions in the entire CRSP universe. In brief, the estimated risk premium of $\triangle PC1$ is negative in all specifications, but is only

[28] Following Novy-Marx (2013), Gross Profitability is the difference between total revenue (Compustat item REVT) and cost of good sold (item COGS), scaled by total asset (item AT), all of which are at the same fiscal year. Following Cooper, Gulen, and Schill (2008), Asset Growth is the percentage change in firms' total assets.

[29] Two factors $\triangle PC1$ and $\triangle PC2$ are motivated by the "recession state variable" hypothesis, and are not return-based factors built from long-short characteristics sorted portfolios. Instead, they are built from macroeconomic forecasts without using stock-level data. In this regard, the threshold of 3 might be a too strong criterion for my exercise.

significant in the first specification. By contrast, the estimated risk premium of $\triangle PC2$ are close to those in Panel A, and are well above 2 for all specifications. Therefore, stock-level analysis provides evidence consistent with preceding portfolio-level results.

4.4 Factor mimicking portfolios

Because the innovations to the level and slope of the recession probability term structure are not returns on traded assets, two factor-mimicking portfolios (FMPs) are constructed to track these innovations by projecting them into a space of excess returns, following Breeden, Gibbons, and Litzenberger (1989). This approach is widely used for non-traded macro factors (Vassalou, 2003; Jagannathan and Wang, 2007; Adrian, Etula, and Muir, 2014, among others). It allows me to expand asset pricing tests to monthly frequency and longer sample periods, which can serve as "out-of-sample" tests for the recession risk model.

Since FMPs are excess returns, the time series regressions' (7) intercepts (alpha) should be jointly zero if the risk factors can span the space of test assets in the mean-variance sense. I report the Gibbons, Ross, and Shanken (1989) (GRS) F-statistic, which formally gauges the joint significance of the intercepts. Economically, the GRS statistic measures the degree of the proximity of the maximum squared Sharpe ratio generated by the candidate risk factors to that generated by test assets in conjunction with the candidate factors. After taking the sampling variation into account, the former should not deviate too much from the latter if the candidates are indeed on the ex-ante mean-variance efficient frontier. Statistically, the GRS time series test is equivalent to a GLS CSR with (traded) factors as additional test assets, which would force the cross-sectionally estimated factor risk premia to equal their time series averages. Thus, factor risk premia are not free parameters but are rather constrained in GRS tests, a prescription also suggested by Lewellen et. al. (2010).

To construct FMPs, I run the following linear projection regressions using the full sample,

$$y_t = a + b'X_t + \epsilon_t,\ y_t \in \{\triangle PC1_t, \triangle PC2_t\} \tag{12}$$

where the portfolio weight b is estimated by OLS. $b'X_t$ is the FMP of y_t, which is the portfolio formed by the basis assets that has the maximum in-sample correlation with y_t. Note that the weight need not be normalized as X_t are excess returns.

Basis assets X_t are given by $[BL, BM, BH, SL, SM, SH, b1, b4, b5, corpr]$ where the first six assets are the six Fama-French size (Small and Big) and B/M (Low, Medium, and High) sorted portfolios, used to construct the Fama-French three factors. $b1$, $b4$, and $b5$ refer to the Fama bond portfolios sorted by maturity, which comprise U.S. T-bills or T-Notes with maturities of 0-1, 3-4, and 4-5 years, respectively. *corpr* is the Ibboston long-term corporate bond portfolio of investment-grade corporate bonds with maturity of more than 10 years.[30] The six size- and B/M-sorted portfolios are chosen because they span a large amount of return spaces. From Table III, $PC1$ is significantly correlated with the default spread and $PC2$ is significantly related to the term spread. Thus, the T-bill and corporate bond portfolios are chosen because they help track the innovations to $PC1$ and $PC2$.

The estimated portfolio weights are given by,

$$b_{\triangle PC1} = [-0.07, -0.35, -0.05, 0.39, -0.58, 0.02, 12.53, -1.85, 0.83, 0.33]$$
$$b_{\triangle PC2} = [-0.02, 0.39, -0.15, 0.19, -0.48, -0.03, -3.05, 3.23, -1.77, -0.22]$$

$\triangle PC1$ FMP takes long positions in small and growth stocks (SL), long-term corporate bonds (corpr), and the short-term T-bills (b1), while it takes short positions in two medium book-to-market portfolios (SM and BM). $\triangle PC2$ FMP sells short the small and medium book-to-market portfolio (SM) and takes a long position on the big and medium book-to-market portfolio (BM), therefore $\triangle PC2$ FMP negatively captures the value premium. In addition, $\triangle PC2$ FMP loads on the term premium by taking a long position on the Treasury bond portfolio with maturity between three and four years (b4) and selling short the short-term T-bill portfolio (b1). The correlation between $\triangle PC1$ ($\triangle PC2$) and $\triangle PC1$ FMP ($\triangle PC2$ FMP) is 0.47 (0.34).

[**Insert Table XIII here**]

Table XIII reports quarterly summary statistics of FMPs and the Fama-French three factors (FF3), Mkt, SMB, and HML. Panel A reports their time series moments and annualized Sharpe ratios. $\triangle PC1$ FMP earns a quarterly risk premium of 0.29%, slightly positive but not significant ($t = 0.5$). By contrast, $\triangle PC2$ FMP earns a significantly risk premium

[30]The Ibboston long-term corporate bond returns are from the website of Amit Goyal `http://www.hec.unil.ch/agoyal/docs/PredictorData2015.xlsx`. I thank Amit Goyal for making the corporate bond returns data available.

of -0.77% ($t = -4.0$). This finding is consistent with results that $\triangle PC1$ is not priced in the cross section but $\triangle PC2$ is negatively priced. The Sharpe ratio of $\triangle PC1$ FMP is tiny, while $\triangle PC2$ FMP has a Sharpe ratio of -0.59, the absolute magnitude of which exceeds that of market excess return (0.35), SMB (0.19), and HML (0.35). Figure 6 plots the sample mean-variance frontier generated by the 10 basis assets. Each factor's position is determined by its absolute Sharpe ratio. $\triangle PC2$ FMP represents the most attractive risk-return tradeoff with the highest Sharpe ratio that is more close to the ex-post tangency portfolio.

Panel B shows that the two FMPs strongly correlate with market and SMB, but only $\triangle PC2$ FMP has a significant negative correlation with HML ($\rho = -0.29$). The time series regressions in Panel C show that $\triangle PC2$ FMP has a CAPM α of -0.59% per quarter ($t = -3.3$) and a FF3 α of -0.29% ($t = -2.2$); therefore, $\triangle PC2$ FMP earns abnormally lower returns, after adjusted risks by the CAPM or FF3. Panel D reports the GRS statistics of time series regressions on the 25 size- and B/M-sorted portfolios for four different models, CAPM, FF3, market with $\triangle PC2$ FMP (Mkt+$\triangle PC2$ FMP), and finally market with $\triangle PC1$ FMP and $\triangle PC2$ FMP ("Rec FMP"). The latter two specifications of the recession risk model outperform the CAPM and have the GRS statistics close to that of FF3; nonetheless, the GRS statistics reject all models.

Table XIV summarizes the cross-sectional tests on the 25 size- and B/M-sorted portfolios in conjunction with the Fama-French 10 industry portfolios for the four models considered in Table XIII. The sample is monthly from July 1963 to December 2014, which has the common starting period in the literature, and extends the previous quarterly data, serving as an "out-of-sample" test for the recession risk model. To ease comparison, all variables are still reported in percentage terms per quarter.

[**Insert Table XIV here**]

For the full model specification "Rec FMP", $\triangle PC2$ FMP is priced and carries a negative risk premium of -0.58% per quarter, while $\triangle PC1$ FMP is not priced. The OLS cross-sectional R^2 of "Rec FMP" (57%) improves substantially relative to the CAPM (-3%) and is greater than 51% of the FF3. The GLS R^2s of "Rec FMP" is again higher than that of FF3, revealing that the model is closer to the ex-post mean-variance efficient frontier. The final column examines a two-factor specification with market and $\triangle PC2$ FMP. Excluding $\triangle PC1$ FMP barely changes the risk premium of risk of $\triangle PC2$ FMP, which is -0.59% per quarter, and does not reduce either OLS or GLS R^2. Regarding the GRS tests, "Rec FMP" and the two-factor specification perform slightly worse than FF3. Overall, consistent with quarterly results in Table VI, the results of the post-1963 monthly sample using factor mimicking portfolios suggest that $\triangle PC2$ is a negatively priced factor and the recession risk model captures the size and value effects as well as the Fama-French three-factor model.

4.5 Currencies and equity index options

Ideally, an asset pricing model should apply to *all* asset classes. However, empirical studies often focus on particular asset classes. Lettau, Maggiori, and Weber (LMW, 2014) show that the downside risk CAPM (DCAPM), which is the static CAPM in conjunction with a market downside risk factor, can reconcile the average excess returns on several asset classes—equities, equity index options, currencies, commodities, and sovereign bonds. In this section, I conduct additional cross-sectional tests of the factor mimicking portfolios in the cross section of returns on S&P 500 Index options and developed countries' currencies.

I focus on these asset classes because their returns vary substantially across business cycles and are exposed to cyclical risk factors, such as durable consumption growth or downside market risk. For instance, Lustig and Verdelhan (2007) rationalize the cross-sectional variation of average foreign currency returns via differences in their exposures to U.S. durable consumption growth. Dahlquist and Hasseltoft (2015) find that past country-level economic fundamentals, including industrial production and trade balance, have strong predictive power for future currency returns. Besides, the two asset classes have attracted much debate on whether their average returns can be reconciled by exposures to systematic risk factors.[31]

I first examine the performance of the factor mimicking portfolios "Rec FMP" in the cross section of S&P 500 Index option returns. Data for S&P 500 Index option returns are from Constantinides, Jackwerth and Savov (2013) (CJS hereafter). CJS construct a large panel of 54 leverage-adjusted S&P 500 Index option portfolios and compute their monthly returns from April 1986 to January 2012. Each portfolio is daily adjusted to have a CAPM beta close to 1 and to maintain constant maturity (30, 60, and 90 days) and moneyness (the

[31] See Constantinides, Jackwerth, and Savov (2013) for S&P 500 Index option returns. See Daniel, Hodrick, and Lu (2014), Lustig and Verdelhan (2007), Burnside et al. (2011), and Dobrynskaya (2014) for the relation between returns to currency carry trade strategies and downside risks.

strike-to-spot ratio).[32] Such leverage adjustment substantially reduces volatility and higher moments of option returns, rendering linear factor models applicable. Since CJS's option returns are highly correlated, following LMW (2014), I select 18 index option portfolios that comprise an equal number of call and put options with same maturities of 30 days, 60 days, and 90 days, and same spot-to-strike ratios of 0.9, 1, and 1.1, respectively.

Table XV reports the results where the 18 selected option portfolios and the 25 size- and B/M-sorted portfolios are test assets. The FF3 and the DCAPM are used as benchmarks.[33]

[**Insert Table XV here**]

In the left panel, the test assets are the 18 option portfolios and market. I impose the constraint that the excess zero-beta rate is zero to increase statistical power, as preliminary analysis shows that even the CAPM performs quite well without this constraint. Starting with "Rec FMP" in the middle, both market excess return and $\triangle PC2$ FMP are priced with correct signs, whereas the risk premium of $\triangle PC2$ FMP is three times higher than the estimated risk premium using equity returns only. In time series regressions, returns to selling deep out-of-money puts have more negative exposures on $\triangle PC2$ FMP than returns on selling in-the-money puts. Thus, consistent with intuition, the former strategy is riskier as it has higher exposure to downside cyclical risk.

For the DCAPM, market excess return and the downside market factor earn significantly positive risk premia, consistent with LMW. The pricing performance of "Rec FMP" is comparable to the DCAPM. "Rec FMP" has a MAPE of 0.32, lower than the MAPE of 0.38 for the DCAPM, while its cross-sectional $\bar{R}^2$ of 0.89 is slightly higher than that of the DCAPM, 0.88. The FF3 model also performs well with low MAPE and high $\bar{R}^2$, however, the estimated market prices of risk reveal that the FF3 has difficulty in reconciling the cross-section of option returns. The estimated risk premium of the size factor is 8.25% per quarter, which is implausibly higher than its time series average, and the value factor has

[32]Note that by construction, returns on put option portfolios are derived from selling put options. For more details about the option data, please refer to the original CJS paper.

[33]My implementation of the downside CAPM is slightly different from LMW (2014) in two dimensions. First, I use simple excess returns instead of log excess returns as in LMW. Second, unlike LMW, I do not impose the constraint that the cross-sectional market price of risk for the market excess return factor is equal to its time series mean. However, this does not mean that, in my implementation, the market risk premium is a free parameter, because I include the market excess return itself as a test asset. In brief, the constraint that I impose is less strict than that imposed by LMW, and consequently the DCAPM under my implementation may have better performance.

a counter-factually negative market price of risk. The large J_T statistics indicate that all these models are mis-specified. Figure 7 displays model-implied average excess returns versus realized average excess returns on test assets. Except for the CAPM, all other models explain the cross sectional variation reasonably well. However, neither can reconcile the well-documented large premium from selling 30-day deep out-of-money put options.

In the right panel, test assets are the 18 option portfolios, 25 size- and B/M-sorted portfolios, and market—44 assets in total. Because the cross-sectional variation of average excess returns is substantial, I drop the constraint that the excess zero-beta rate is zero, although including it does not alter the conclusion. Starting with "Rec FMP", both $\triangle PC1$ FMP and $\triangle PC2$ FMP are significantly priced in the cross section with negative market prices of risk of -3.86% and -0.81% per quarter, although the risk premium of $\triangle PC1$ FMP is too high relative to its time series mean. The DCAPM performs quite well in the cross-section of equity and equity index option returns. The downside market factor is priced and its risk premium, 4.19% per quarter, does not deviate too much from the risk premium 4.63% per quarter, estimated using options only. CJS also find that a similar specification with market prices of risk that are constrained to equal the prices of risk estimated in the cross section of stock returns performs well in the joint cross section of equity and index option returns. Diagnostic statistics show that "Rec FMP" underperforms the DCAPM with a larger MAPE, a lower $\bar{R}^2$, and a significantly negative zero-beta rate of -3% per quarter.

I then investigate whether $\triangle PC2$ FMP is priced in the currency returns and whether "Rec FMP" can reconcile the cross-sectional variation of currency risk premia. The sample of currency returns is monthly from January 1974 to March 2010, also from LMW (2014). LMW construct five interest rate-sorted portfolios of currencies of developed countries.[34] For each currency, LMW compute its monthly bilateral log return in excess of the log return on the U.S. dollar. Each portfolio is a zero-cost carry trade portfolio that longs currencies of developed countries other than U.S., while funding the position by borrowing U.S. dollars. It is well known that the counter-level risk-free rate is the most informative characteristic that positively predicts future currency returns (Lustig, Roussanov, and Verdelhan, 2011). Table XVI presents the pricing performance of "Rec FMP" on the cross section of currency

[34]LMW construct another set of carry trade portfolios, formed by currencies of both developed and developing countries. The cross-sectional tests using these portfolios are qualitatively similar to the results shown in the main text.

and equity portfolios.

[Insert Table XVI here]

In the left panel, test assets are the five currency portfolios and market. I again impose the constraint that the excess zero-beta rate is zero because of the small size of the cross section. The DCAPM captures most of the cross-sectional variation of carry trade returns and has the lowest average absolute pricing error. For the FF3 model, both the size and value factors are not priced in the cross section and the model has the largest MAPE of 0.4, and the lowest $\bar{R}^2$ of 0.5. This result is consistent with previous studies which document that carry trade strategies have only limited unconditional exposures to equity market risks, measured by the factor exposures on the FF3 model (Lustig and Verdelhan, 2007; Burnside et al., 2011; Daniel, Hodrick, and Lu, 2014). Turning to "Rec FMP", similar to the results of index option returns, both market and $\triangle PC2$ FMP are priced with correct signs of market prices of risk, albeit the risk premium of $\triangle PC2$ FMP, -3.07%, is too large compared to its time series average. The average factor exposure on $\triangle PC2$ FMP is 0.11 for the two low interest rate carry trade portfolios, and is slightly below 0 for the two high interest rate portfolios. The factor exposure spread, -0.12, is significant at 5% level. Thus the carry trade returns have unconditional exposures to equity and bond market risk, but are only exposed to the part correlated with shocks to investors' perceived recession risk.

The right panel presents the results for the joint cross section of the 5 currency portfolios, the 25 size- and B/M-sorted portfolios, and market—31 assets in total. Again, I drop the restriction that the excess zero-beta rate is zero. Starting with "Rec FMP", both $\triangle PC1$ FMP and $\triangle PC2$ FMP are significantly priced in the cross section with large market prices of risk of -3.91% and -0.85% per quarter. The estimated market price of risk of $\triangle PC2$ FMP is close to its time series average, and to the estimate in the joint cross section of index options and stock returns. Diagnostic statistics in Panel B reveal that "Rec FMP" outperforms the DCAPM and the FF3 model, with the only exception that the excess zero-beta rate of "Rec FMP" is significantly positive. "Rec FMP" has the smallest MAPE of 0.32 and the largest cross-sectional $\bar{R}^2$ of 0.81 among all models. Figure 10 plots the model-implied average excess returns versus realized average excess returns. The 31 assets under "Rec FMP" fall closer to the 45-degree line than do the assets under the DCAPM and the FF3 model.

To conclude, the factor mimicking portfolio of $\triangle PC2$ is negatively priced and helps reconcile the cross-sectional variation of average excess returns on equity, equity index option and developed countries' currencies. The factor mimicking portfolios of the recession risk model have performance comparable to the DCAPM of Lettau, Maggiori, and Weber (2014).

5 Conclusion

Motivated by the time-varying duration of recessions, this paper studies a new macro-factor asset pricing model, which links assets' risk premia to their exposures to time-varying investor concern over future recessions. Using the Survey of Professional Forecasters database, I measure the investor concern by the level and slope of the term structure of recession probabilities. The innovation to the slope of the term structure is a negatively priced risk factor with an economically large and significant risk premium in a wide range of test assets, consistent with how the slope predicts long-run macroeconomic activity and labor income. A linear factor model, including market excess return and the innovations to the slope, explains at least more than half of the cross-sectional variation of average excess returns on equity portfolios sorted on size, book-to-market equity, past long term return, and asset growth. These findings are robust to the recent critique raised by Lewellen, Nagel and Shanken (2010) on evaluating asset pricing models. GMM Stochastic Discount Factor tests confirm that the innovation to the slope of the term structure helps price the test assets in the presence of risk factors in existing macro-factor models.

I argue that the innovation to the slope of the term structure is negatively priced because the slope of the term structure is a recession state variable that can predict long-run macroeconomic activity and labor market conditions. Investors may lose their jobs and business in recessions and hence prefer assets whose cash flows are less sensitive to news of future recessions to hedge their labor income risks. Consistent with this argument, I document that future profitability changes of value firms are more exposed to temporal variations in the slope than growth firms. In addition, returns on risky assets, such as value firms, past long term losers, and risky corporate bonds have more negative exposures on the innovation to the slope than returns on securities with characteristics in the opposite direction. Consequently, investors are less willing to hold these risky assets because they cannot help investors better smooth consumption and hedge labor income risks. Finally, I show that the factor mimicking portfolios of the level and slope factor help explain the joint cross section of returns on equities, equity index options, and currencies and have comparable performance to the downside risk CAPM of Lettau, Maggiori, and Weber (2014). My findings support a risk-based explanation of the value premium, and further suggest that an economic source of risk premia on asset classes considered could be attributed to time-varying investor concern over future recessions that is priced.

This paper focuses on the particular term structure of macroeconomic forecasts—recession probabilities. However, there are term structures of forecasts on other important aspects of the macroeconomy, for instance, unemployment. Exploring the information in these macroeconomic forecasts for asset pricing could be a fruitful research area in the future.

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Table I: **Descriptive Statistics of SPF Recession Probabilities**

This table reports descriptive statistics (in percentage terms) of recession probability forecasts, taken from the Survey of Professional Forecasters (SPF), and other macroeconomic variables used in empirical analyses. $Rec_{t,i}, i \in \{0,1,2,3\}$ refers to the probability of a decline in U.S. real GDP in quarter-$t+i$, forecast at quarter-t. Mathematically, $Rec_{t,i}$ is defined as $Rec_{t,i} \equiv Pr_t(GDP_{t+i} < GDP_{t+i-1})$, where GDP_{t+i} denotes the level of U.S. real GDP in quarter-$t+i$. The macroeconomic variables include the term spread (TERM), default spread (DEF), the log dividend-price ratio on the CRSP value-weighted index (d/p), the quarterly excess returns on the CRSP value-weighted index (Mkt), and growth rates of the industrial production index ($\triangle IP$), quarterly real per capita consumption ($\triangle c$), quarterly real GDP ($\triangle GDP$), and quarterly real per capita labor income (l), all of which are seasonally adjusted, as introduced in Section 2. Panel A displays the sample moments of recession probabilities and macroeconomic variables, including mean, standard deviation, median, skewness, kurtosis, minimum, maximum, first-order autocorrelation ($AC(1)$), and fifth-order autocorrelation ($AC(5)$). Panel B reports their time series correlations. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters in total.

Panel A: Descriptive Statistics (%)

	Mean	Std	Median	Skew	Kurt	Min	Max	AC(1)	AC(5)	Obs
Recession Probabilities										
Rec_0	19.21	22.92	9.66	1.83	2.41	0.52	94.41	0.74	0.06	186
Rec_1	19.24	16.33	12.85	1.73	2.53	2.16	74.78	0.78	0.14	186
Rec_2	18.10	10.66	15.27	1.72	3.04	4.03	58.80	0.77	0.18	186
Rec_3	17.20	6.53	16.43	0.86	0.70	4.56	36.31	0.77	0.29	186
Rec_4	17.27	5.86	16.74	0.51	-0.29	4.51	33.34	0.78	0.41	182
Macro Variables										
$\triangle IP$	0.55	1.65	0.74	-1.57	5.14	-7.31	4.13	0.48	-0.14	186
$\triangle c$	0.44	0.44	0.46	-0.45	0.92	-1.12	1.55	0.52	0.06	186
$\triangle GDP$	0.68	0.82	0.73	-0.30	2.05	-2.14	3.81	0.32	-0.03	186
$\triangle l$	0.33	0.85	0.38	-0.49	1.92	-2.96	3.27	0.02	-0.03	186
TERM	1.11	1.21	1.21	-0.40	-0.07	-3.07	3.33	0.86	0.44	186
DEF	1.10	0.45	0.96	1.84	4.77	0.55	3.38	0.84	0.37	186
d/p	0.99	0.42	1.02	-0.14	-0.91	0.11	1.77	0.98	0.87	186
Mkt	1.54	8.87	2.33	-0.48	0.59	-26.85	23.37	0.07	0.01	186

Panel B: Correlation Matrix

	Rec_1	Rec_2	Rec_3	Rec_4	$\triangle IP$	$\triangle c$	$\triangle GDP$	$\triangle l$	TERM	DEF	d/p	Mkt
Rec_0	0.90	0.68	0.35	-0.05	-0.65	-0.48	-0.62	-0.34	-0.06	0.57	0.36	-0.06
Rec_1	1.00	0.89	0.55	0.09	-0.66	-0.53	-0.59	-0.38	-0.19	0.55	0.39	-0.10
Rec_2	0.89	1.00	0.80	0.35	-0.56	-0.48	-0.48	-0.37	-0.35	0.40	0.40	-0.12
Rec_3	0.55	0.80	1.00	0.79	-0.39	-0.32	-0.31	-0.27	-0.43	0.25	0.37	-0.11
Rec_4	0.09	0.35	0.79	1.00	-0.08	-0.01	0.02	-0.02	-0.36	0.08	0.29	-0.10

Table II: **Forecasting NBER Recessions (Q4/1968-Q2/2014, 183 Quarters)**

This table reports the maximum likelihood estimates and associated z-statistics (in parentheses) of probit predictive regressions of future NBER recession dummies on current SPF recession probability forecasts (in percentage terms). The dependent variable $D_{t+i},\ i \in \{0,1,2,3\}$ is a dummy that is defined as follows,

$$D_{t+i} = \begin{cases} 1, \text{quarter } t+i \text{ is in an NBER recession} \\ 0, \text{otherwise} \end{cases}$$

The probit regression is specified as follows,

$$p_{t,i} \equiv Pr(D_{t+i} = 1|\mathcal{F}_t) = \Phi(\beta_0 + \beta_1 Rec_{t,i} + \beta_2 Rec_{t,i+1} + \gamma X_t)$$
$$\log \ell = \sum_{t=1}^{T} D_{t+i} log p_{t,i} + (1 - D_{t+i}) log(1 - p_{t,i})$$

where $Pr(D_{t+i} = 1|\mathcal{F}_t)$ is the probability that quarter-$t+i$ is in an NBER recession, conditional on quarter-t information $\mathcal{F}_t$, Φ is the cumulative distribution function of the standard normal and X_t are control variables including the observations of the term spread (TERM) and the CRSP value-weighted index return (Mkt) in quarter-t. The main explanatory variables are $Rec_{t,i}$ and $Rec_{t,i+1}$, where $Rec_{t,i}$ refers to the quarter-t SPF forecasts of the probability of a decline in U.S. real GDP level in quarter-$t+i$. $\log \ell$ is the log likelihood function of the model. HL (p-value) is the p-value of the Hosmer-Lemeshow χ^2 statistic testing the goodness-of-fit of the regression. Pseudo R^2 is defined by Estrella and Mishkin (1998), which takes a value between 0 ("no fit") and 1 ("perfect fit"). The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the second quarter of 2014 (2014Q2), 183 quarters in total.

	SPF Only				SPF & Controls		
	D_t	D_{t+1}	D_{t+2}	D_{t+3}	D_{t+1}	D_{t+2}	D_{t+3}
$Rec_{t,0}$	**0.047**						
z-stat	(3.86)						
$Rec_{t,1}$	0.011	**0.053**			**0.070**		
z-stat	(0.61)	(3.40)			(3.88)		
$Rec_{t,2}$		0.000	**0.078**		-0.025	**0.082**	
z-stat		(0.00)	(4.13)		(0.89)	(3.75)	
$Rec_{t,3}$			-0.051	**0.052**		**-0.083**	0.012
z-stat			-(1.58)	(3.09)		(2.24)	(0.60)
TERM					-0.202	**-0.378**	**-0.581**
z-stat					-(1.53)	-(2.93)	-(4.38)
Mkt					**-0.066**	**-0.069**	**-0.041**
z-stat					-(3.87)	-(4.10)	-(2.67)
Pseudo R^2	0.53	0.33	0.18	0.05	0.47	0.38	0.26
HL (p-value)	0.14	0.17	0.13	0.08	0.57	0.91	0.73
Obs	183	182	181	180	182	181	180

Table III: **Descriptive Statistics of Principal Components of the Term Structure of SPF Recession Probability Forecasts**

This table reports summary statistics of the first and second principal components, $PC1$ and $PC2$, of the term structure of SPF recession probabilities (in percentage terms). Panel A displays the sample moments, including mean, standard deviation, median, skewness, kurtosis, minimum, maximum, and first-order autocorrelation $AC(1)$ (whole sample only) over the whole sample and over recessions identified by the NBER. Panel B reports the contemporaneous correlations and p-values (in parentheses) of $PC1$ and $PC2$ with macroeconomic variables, including the term spread (TERM), default spread (DEF), log dividend-price ratio on the CRSP value-weighted index (d/p), quarterly excess returns on the CRSP value-weighted index (Mkt), and quarterly growth rates of the industrial production index ($\triangle IP$), quarterly real per capita consumption ($\triangle c$), final revised quarterly real GDP ($\triangle GDP$), and quarterly real per capita labor income (l), all of which are seasonally adjusted, as described in Section 2. Panel C reports the estimation results of the VAR(1) model of $PC1$ and $PC2$. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters in total.

Panel A: Sample Moments of Principal Components

	Mean	Std	Median	Skew	Kurt	Min	Max	AC(1)	Obs
All									
PC1	32.79	28.94	20.63	1.76	2.46	4.19	130.29	0.79	186
PC2	15.41	9.56	14.6	0.75	2.38	-10.94	51.47	0.59	186
NBER Recessions									
PC1	82.64	28.27	74.49	0.31	-1.27	41.08	130.29	-	29
PC2	11.84	13.59	10.03	0.62	0.14	-10.94	46.37	-	29

Panel B: Contemporaneous Correlation with Macro Variables

	TERM	DEF	d/p	Mkt	$\triangle IP$	$\triangle c$	$\triangle GDP$	$\triangle l$
PC1	-0.15	0.57	0.39	-0.08	-0.67	-0.52	-0.62	-0.38
p-value	(0.05)	(0.00)	(0.00)	(0.27)	(0.00)	(0.00)	(0.00)	(0.00)
PC2	-0.41	-0.07	0.14	-0.10	-0.03	-0.10	0.05	-0.11
p-value	(0.00)	(0.32)	(0.05)	(0.18)	(0.64)	(0.18)	(0.54)	(0.14)

Panel C: VAR(1) of Principal Components

	$PC1_{t+1}$	$PC2_{t+1}$
Intercept	-7.64	8.69
t-stat	-(3.12)	(7.13)
$PC1_t$	0.78	-0.06
t-stat	(20.25)	-(3.31)
$PC2_t$	0.97	0.57
t-stat	(8.33)	(9.90)
R^2	0.72	0.37
Obs	185	185

Table IV: **Forecasting Real Economic Activity and Labor Income Growth (Q4/1968-Q1/2015, 186 Quarters)**

This table reports ordinary least square (OLS) estimates, t-statistics (in parentheses), and adjusted OLS R-squares $\bar{R}^2s$ of predictive regressions of future seasonally adjusted quarterly growth rates of the industrial production index (IP), real per capita consumption (c), real GDP (GDP), and real per capita labor income (l) on $PC1$ and $PC2$. $PC1$ and $PC2$ are the first principal component (level) and the second principal component (slope) of the term structure of SPF recession probabilities (in percentage terms). The predictive regression is specified as follows,

$$y_{t\to t+h} = \alpha(h) + b1(h)PC1_t + b2(h)PC2_t + \theta(h)X_t + \epsilon_{t,h}$$

where $y_{t\to t+h} \equiv 400/h$ (log y_{t+h} − log y_t) is the annualized continuously compounded growth rate of y_t from quarter t to quarter $t+h$. The macro control variable X_t consists of the term spread (TERM), default spread (DEF), three-month T-bill rate ($y^{(3m)}$), CRSP value-weighted index excess return (Mkt), log dividend-price ratio on the CRSP value-weighted index (d/p), and lagged one-period growth rate $y_{t-1\to t}$. "Y" ("N") in the row labeled "Macro Control" refers to the model specification where X_t is included (excluded) in the regression. The definition of macro variables is introduced in Section 2. The sample of predictive regressions is quarterly from 1968Q4 to 2015Q1. The forecasting horizon h takes values of 1, 4, 8, 12, and 16. t-statistics are adjusted by Newey and West (1987) standard errors with one lag when the forecasting horizon h is 1, and by the Hodrick (1992) standard errors for $h > 1$ when the observations of dependent variables are overlapped.

Panel A: Industrial Production Index Growth										
	$\triangle IP_{t\to t+1}$		$\triangle IP_{t\to t+4}$		$\triangle IP_{t\to t+8}$		$\triangle IP_{t\to t+12}$		$\triangle IP_{t\to t+16}$	
$PC1_t$	-0.096	-0.024	-0.056	-0.051	-0.013	-0.022	0.001	-0.005	0.009	0.011
t-stat	-(4.35)	-(1.10)	-(2.96)	-(2.53)	-(1.05)	-(1.78)	(0.08)	-(0.60)	(1.26)	(1.69)
$PC2_t$	-0.167	-0.105	-0.120	-0.058	-0.139	-0.095	-0.111	-0.079	-0.064	-0.039
t-stat	-(3.21)	-(2.21)	-(2.66)	-(1.56)	-(3.31)	-(2.78)	-(3.58)	-(3.03)	-(2.75)	-(1.90)
Macro Control	N	Y	N	Y	N	Y	N	Y	N	Y
$\bar{R}^2$	0.23	0.42	0.17	0.39	0.15	0.34	0.16	0.36	0.10	0.31
Obs	186	186	183	183	179	179	175	175	171	171
Panel B: Per Capita Real Consumption Growth										
	$\triangle c_{t\to t+1}$		$\triangle c_{t\to t+4}$		$\triangle c_{t\to t+8}$		$\triangle c_{t\to t+12}$		$\triangle c_{t\to t+16}$	
$PC1_t$	-0.023	-0.013	-0.015	-0.012	-0.005	-0.006	0.000	0.000	0.002	0.003
t-stat	-(4.52)	-(2.32)	-(3.44)	-(2.62)	-(1.62)	-(1.71)	(0.04)	(0.16)	(0.82)	(1.59)
$PC2_t$	-0.033	-0.023	-0.037	-0.029	-0.037	-0.031	-0.027	-0.024	-0.014	-0.016
t-stat	-(2.18)	-(1.51)	-(3.23)	-(2.76)	-(3.55)	-(3.33)	-(3.35)	-(3.20)	-(2.38)	-(2.58)
Macro Control	N	Y	N	Y	N	Y	N	Y	N	Y
$\bar{R}^2$	0.17	0.33	0.17	0.37	0.10	0.31	0.06	0.34	0.02	0.37
Obs	186	186	183	183	179	179	175	175	171	171
Panel C: Real GDP Growth										
	$\triangle GDP_{t\to t+1}$		$\triangle GDP_{t\to t+4}$		$\triangle GDP_{t\to t+8}$		$\triangle GDP_{t\to t+12}$		$\triangle GDP_{t\to t+16}$	
$PC1_t$	-0.047	-0.047	-0.027	-0.031	-0.009	-0.016	-0.001	-0.007	0.004	0.001
t-stat	-(5.60)	-(4.46)	-(3.55)	-(4.07)	-(1.41)	-(2.35)	-(0.26)	-(1.41)	(0.99)	(0.27)
$PC2_t$	-0.092	-0.087	-0.061	-0.040	-0.066	-0.048	-0.058	-0.047	-0.033	-0.028
t-stat	-(3.61)	-(3.18)	-(2.92)	-(1.81)	-(3.51)	-(2.78)	-(3.60)	-(3.34)	-(2.70)	-(2.38)
Macro Control	N	Y	N	Y	N	Y	N	Y	N	Y
$\bar{R}^2$	0.24	0.29	0.18	0.35	0.15	0.33	0.15	0.37	0.08	0.36
Obs	186	186	183	183	179	179	175	175	171	171
Panel D: Real Labor Income Growth										
	$\triangle l_{t\to t+1}$		$\triangle l_{t\to t+4}$		$\triangle l_{t\to t+8}$		$\triangle l_{t\to t+12}$		$\triangle l_{t\to t+16}$	
$PC1_t$	-0.039	-0.053	-0.023	-0.028	-0.006	-0.015	0.001	-0.004	0.004	0.002
t-stat	-(3.64)	-(5.02)	-(2.64)	-(3.46)	-(1.05)	-(2.46)	(0.33)	-(1.04)	(1.15)	(0.44)
$PC2_t$	-0.078	-0.076	-0.080	-0.070	-0.057	-0.049	-0.041	-0.039	-0.021	-0.021
t-stat	-(2.83)	-(2.66)	-(3.65)	-(3.41)	-(2.69)	-(2.64)	-(2.54)	-(2.63)	-(1.90)	-(1.95)
Macro Control	N	Y	N	Y	N	Y	N	Y	N	Y
$\bar{R}^2$	0.15	0.19	0.26	0.34	0.13	0.24	0.09	0.21	0.04	0.20
Obs	186	186	183	183	179	179	175	175	171	171

Table V: **Forecast the Term Structure of SPX Option Implied Volatility (VIX) Indices (Q1/1990-Q1/2015, 102 Quarters)**

This table presents ordinary least square (OLS) estimates, t-statistics (in parentheses), and adjusted OLS R-squares $\bar{R}^2$ of predictive regressions of the Chicago Board Options Exchange (CBOE) VIX index and long-term VIX indices on $PC1$ and $PC2$. The squared CBOE VIX index is the (annualized) conditional expected quadratic variation of the S&P 500 Index over the subsequent 30 days under the risk-neutral measure. The long-term VIX indices with maturities of 3, 6, and 12 months are the (annualized) conditional expected quadratic variations of the S&P 500 Index over the subsequent 3, 6, and 12 months under the risk-neutral measure. Both the CBOE VIX index and long-term VIX indices are estimated from S&P 500 European options prices in a model-free manner. $PC1$ and $PC2$ are the first and second principal components of the term structure of SPF recession probabilities (in percentage terms). The specification of the predictive regressions is as follows,

$$\log VIX_{\tau,t+h} = \alpha(\tau,h) + b1(\tau,h)PC1_t + b2(\tau,h)PC2_t + \theta(\tau,h)X_t + \epsilon_{\tau,t+h}$$

where t is measured in quarters, the forecasting horizon h is one quarter, and $\log VIX_{\tau,t+h}$ is the quarter-$t+h$ observation of the logarithm of a VIX index with maturity τ. The control variable $X(t)$ consists of the quarter-t observations of the term spread, default spread, and log returns on the S&P 500 Index in the last month of quarter-t. The sample of the CBOE VIX index is quarterly from January 1990 to April 2015 (101 quarters). The sample of the long-term VIX indices is quarterly from 1996 to August 2013 (70 quarters). t-statistics are adjusted by Newey-West standard errors with six lags. The CBOE VIX index is taken from CBOE and long-term VIX indices are taken from Travis L. Johnson's homepage .

1-Quarter Ahead VIX Indices								
	$logVIX_{1,t+1}$	$logVIX_{1,t+1}$	$logVIX_{3,t+1}$	$logVIX_{3,t+1}$	$logVIX_{6,t+1}$	$logVIX_{6,t+1}$	$logVIX_{12,t+1}$	$logVIX_{12,t+1}$
$PC1_t$	0.001	0.000	0.004	0.002	0.002	0.000	0.001	0.000
t-stat	(0.67)	-(0.18)	(1.55)	(0.90)	(0.99)	(0.33)	(0.70)	-(0.28)
$PC2_t$	0.014	0.008	0.023	0.011	0.020	0.009	0.020	0.010
t-stat	(2.14)	(2.07)	(2.69)	(2.21)	(2.73)	(2.03)	(3.05)	(2.10)
lagged Y		0.583		0.613		0.656		0.631
t-stat		(6.96)		(5.85)		(6.55)		(8.02)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
$\bar{R}^2$	0.23	0.46	0.24	0.49	0.25	0.54	0.37	0.59
Obs	101	100	70	69	70	69	70	69

Table VI: **Pricing Quarterly Excess Returns on the Fama-French 25 Size- and Book-to-market-sorted Portfolios (Q1/1969-Q4/2014, 184 Quarters)**

This table presents estimates of cross-sectional regressions of average excess returns on the Fama-French 25 size- and book-to-market-sorted portfolios and the CRSP value-weighted index on their unconditional factor exposures. Each model is estimated by a cross-sectional regression $E_T[R^e_{i,t}] = \alpha + \beta^i_{fac}\lambda_{fac} + \xi_i,\ i = 1, ..., N$ where $E_T[R^e_{i,t}]$ is average excess return on asset i, α is the excess zero-beta rate, and ξ_i is the pricing error of asset i. β^i_{fac} and λ_{fac} represent factor exposures of asset i and factor risk premia, respectively. Mkt denotes market excess return. $PC1$ and $PC2$ are the first (level) and second principal components (slope) of the term structure of SPF recession probabilities (in percentage terms). $\triangle PC1$ and $\triangle PC2$ are the innovations to $PC1$ and $PC2$, estimated by a first-order VAR over the entire sample. $\triangle TERM$ and $\triangle DEF$ refer to the first difference of the term spread and the default spread. Panel A reports estimated prices of risk with both Fama-MacBeth and GMM-type t-statistics. Panel B reports diagnostic statistics of cross-sectional regressions, including mean absolute pricing errors (MAPEs, $\frac{1}{N}\sum|\xi_i|$), adjusted cross-sectional R-squares $\bar{R}^2$, and Hansen's over-identification J_T statistics, which gauge the joint significance of ξ_i. p-values of the J_T statistics are shown in the row labeled "p-value". The sample is quarterly from 1969Q1 to 2014Q4 (184 quarters). The data for the one-month T-bill and the 25 Fama-French size- and book-to-market-sorted portfolios are from Kenneth French's web site. Risk premia are reported in percentage terms per quarter.

25 Size- and B/M-sorted Portfolios + Mkt					
Panel A: Prices of Risk					
	I	**II**	**III**	**IV**	**V**
Intercept	3.11	2.90	3.23	3.57	2.99
t-FM	(3.17)	(2.91)	(3.28)	(3.44)	(3.38)
t-GMM	(3.16)	(2.65)	(2.67)	(2.19)	(2.32)
Mkt	-0.92	-0.76	-1.46	-1.88	-1.35
t-FM	-(0.79)	-(0.64)	-(1.26)	-(1.55)	-(1.22)
t-GMM	(0.00)	-(0.60)	-(1.09)	-(1.09)	-(0.92)
$\triangle \boldsymbol{PC1}$		-6.16		11.73	9.29
t-FM		-(1.32)		(2.90)	(2.60)
t-GMM		-(1.21)		(1.89)	(1.90)
$\triangle \boldsymbol{PC2}$			-4.99	-7.47	-4.69
t-FM			-(2.65)	-(3.50)	-(2.46)
t-GMM			-(2.19)	-(2.28)	-(2.02)
$\triangle \boldsymbol{Term}$					0.44
t-FM					(2.65)
t-GMM					(1.94)
$\triangle \boldsymbol{Def}$					0.06
t-FM					(1.09)
t-GMM					(0.77)
Panel B: Test Diagnostics					
	I	**II**	**III**	**IV**	**V**
MAPE	0.49	0.45	0.27	0.25	0.26
$\bar{R}^2$	0.04	0.08	0.57	0.64	0.65
Over-identification J_T	86.05	71.35	52.17	30.74	43.36
p-value	0.00	0.00	0.00	0.10	0.00

Table VII: **Pricing Quarterly Excess Returns on Other Equity and Bond Portfolios (Q1/1969-Q4/2014, 184 Quarters)**

This table presents estimates of market prices of risk of the recession risk model using cross-sectional regressions of average excess returns on three sets of test assets. Panel A reports the estimates using the 25 size- and book-to-market-sorted portfolios, 6 Fama Treasury bond portfolios sorted by maturity, and 5 corporate bond portfolios sorted by credit spreads. Panel B reports the estimates using the 25 size and long-term reversal-sorted portfolios. Panel C reports the estimates using the 25 size- and investment-intensity-sorted portfolios. Each model is estimated by a cross-sectional regression $E_T[R^e_{i,t}] = \alpha + \beta^i_{fac}\lambda_{fac} + \xi_i$, $i = 1, ..., N$ where $E_T[R^e_{i,t}]$ is the average excess return on asset i, α is the excess zero-beta rate, and ξ_i is the pricing error. β^i_{fac} and λ_{fac} represent the factor exposures of asset i and factor risk premia, respectively. Factors are Mkt, $\triangle PC1$, and $\triangle PC2$. The table reports estimated market prices of risk associated with Fama-MacBeth t-statistics, as well as GMM-type t-statistics (in parentheses), and other diagnostic statistics of cross-sectional regressions, including mean absolute pricing errors (MAPEs, $\frac{1}{N}\sum|\xi_i|$), adjusted cross-sectional R-squares $\bar{R}^2$, and Hansen's over-identification J_T statistics, which gauge the joint significance of ξ_i. The J_T statistics follow χ^2 distributions with p-values shown in parentheses. The sample is quarterly from 1976Q1 to 2010Q3 for Panel A, and from 1969Q1 to 2014Q4 for Panels B and C. The data for the 6 Treasury bond portfolios and 5 corporate bond portfolios are from the CRSP and Nozawa (2012), respectively. Other data are from Kenneth French's web site. Risk premia are reported in percentage terms per quarter.

	Intercept (t-FM) (t-GMM)	**Mkt** (t-FM) (t-GMM)	$\triangle PC1$ (t-FM) (t-GMM)	$\triangle PC2$ (t-FM) (t-GMM)	**MAPE**	$\bar{R}^2$	J_T (**p-value**)
Panel A: 25 Size–B/M Sorted Portfolios + 5 Corporate + 6 Treasury Portfolios							
I	0.57	1.73			0.57	0.54	157.96 (0.00)
	(4.04)	(2.22)					
	(3.96)	(0.02)					
II	0.62	1.76	-6.08		0.58	0.55	140.89 (0.00)
	(4.07)	(2.26)	-(1.89)				
	(3.77)	(2.24)	-(1.77)				
III	0.54	1.20		-4.44	0.45	0.65	116.33 (0.00)
	(3.82)	(1.62)		-(2.71)			
	(3.21)	(1.59)		-(2.32)			
IV	0.56	1.24	-0.05	-4.03	0.45	0.64	120.89 (0.00)
	(3.64)	(1.68)	-(0.01)	-(2.33)			
	(3.12)	(1.66)	-(0.01)	-(2.03)			
Panel B: 25 Size–Long-Term Reversal Sorted Portfolios							
I	1.31	0.87			0.40	0.04	60.11 (0.00)
	(1.56)	(0.76)					
	(1.58)	(0.00)					
II	1.36	0.83	-6.63		0.37	0.11	71.15 (0.00)
	(1.65)	(0.74)	-(1.38)				
	(1.38)	(0.65)	-(1.13)				
III	2.56	-0.67		-3.84	0.26	0.49	53.67 (0.00)
	(3.39)	-(0.63)		-(2.07)			
	(3.04)	-(0.66)		-(1.86)			
IV	2.68	-0.83	4.15	-4.46	0.25	0.48	48.50 (0.00)
	(3.27)	-(0.77)	(1.07)	-(2.26)			
	(2.80)	-(0.71)	(0.96)	-(2.00)			
Panel C: 25 Size–Investment Sorted Portfolios							
I	2.98	-0.78			0.48	0.02	119.13 (0.00)
	(3.54)	-(0.71)					
	(3.52)	(0.00)					
II	3.08	-0.91	-8.50		0.41	0.17	85.83 (0.00)
	(3.72)	-(0.85)	-(1.87)				
	(3.18)	-(0.77)	-(1.61)				
III	3.94	-2.05		-5.54	0.26	0.59	72.22 (0.00)
	(4.86)	-(2.00)		-(2.73)			
	(3.78)	-(1.70)		-(2.15)			
IV	4.07	-2.23	7.22	-6.95	0.25	0.60	55.96 (0.00)
	(4.83)	-(2.12)	(1.89)	-(3.12)			
	(3.35)	-(1.64)	(1.34)	-(2.20)			

Table VIII: **Robustness Test: quarterly excess returns on the Fama-French 25 size- and book-to-market-sorted portfolios and the 30 industry portfolios (Q1/1969-Q3/2014, 183 Quarters)**

This table presents estimates of cross-sectional regressions using the Fama-French 25 size- and book-to-market-sorted portfolios and the CRSP value-weighted index alone, and in conjunction with the 30 Fama-French industry portfolios. Each model is estimated by a cross-sectional regression $E_T[R^e_{i,t}] = \alpha + \beta^i_{fac}\lambda_{fac} + \xi_i,\ i = 1, ..., N$ where $E_T[R^e_{i,t}]$ is the average excess return on asset i, α is the excess zero-beta rate, and ξ_i is the pricing error. β^i_{fac} and λ_{fac} represent the factor exposures of asset i and factor risk premia, respectively. Rec refers to the recession risk model (Mkt, $\triangle PC1$, $\triangle PC2$), CC-CAY is the conditional consumption-CAPM of Lettau and Ludvigson (2001), where the consumption-wealth ratio CAY is the conditioning variable, D-CCAPM is the durable consumption-CAPM of Yogo (2006), including the growth rate of durable consumption $\triangle c_{dur}$ as a risk factor, U-CCAPM is the ultimate consumption risk model of Parker and Julliard (2005), with current and future 11-quarter real per capita consumption growth $\triangle c_{0\rightarrow 11}$ as the only risk factor, CCAPM is the consumption-CAPM, HL is an intertemporal CAPM of Hahn and Lee (2006), and FF3 is the Fama and French (1993) three-factor model. The table reports estimated market prices of risk, GMM-type t-statistics (in parentheses) and other diagnostic statistics, including mean absolute pricing errors (MAPEs, $\frac{1}{N}\sum|\xi_i|$), OLS adjusted cross-sectional R-squares $\bar{R}^2_{OLS}$, and GLS cross-sectional R-squares R^2_{GLS}, and Hansen's over-identification J_T statistics, which gauge the joint significance of ξ_i. J_T statistics follow χ^2 distributions with p-values shown in parentheses. The sample is quarterly from 1969Q1 to 2014Q3 (183 quarters) except for the D-CCAPM (1969Q1 to 2001Q4) and U-CCAPM (1969Q1 to 2012Q3), constrained by data availability. Risk premia are reported in percentage terms per quarter.

Model	**Variables**				MAPE	$\bar{R}^2_{OLS}$	R^2_{GLS}	J_T (p-value)
Rec	**Inter.**	$\boldsymbol{Mkt}$	$\boldsymbol{\triangle PC1}$	$\boldsymbol{\triangle PC2}$				
FF25 + Mkt	3.62 (2.20)	-1.95 (-1.12)	11.9 (1.90)	-7.52 (-2.27)	0.25	0.64	0.15	30.41 (0.11)
FF25 + Mkt + 30 Ind.	2.80 (3.20)	-0.98 (-0.92)	4.54 (1.50)	-2.99 (-1.99)	0.39	0.19	0.05	148.96 (0.00)
CC-CAY	**Inter.**	**CAY**	$\boldsymbol{\triangle c}$	**CAY** $\boldsymbol{* \triangle c}$				
FF25 + Mkt	2.45 (1.48)	1.50 (1.09)	-0.11 (-0.25)	2.76 (1.95)	0.31	0.57	0.02	23.29 (0.39)
FF25 + Mkt + 30 Ind.	2.13 (2.64)	0.70 (1.02)	-0.10 (-0.54)	1.09 (1.87)	0.43	0.11	0.04	131.32 (0.00)
D-CCAPM*	**Inter.**	$\boldsymbol{Mkt}$	$\boldsymbol{\triangle c}$	$\boldsymbol{\triangle d}$				
FF25 + Mkt	3.33 (1.82)	-1.51 (-0.80)	0.09 (0.37)	-0.57 (-1.05)	0.35	0.56	0.05	29.59 (0.13)
FF25 + Mkt + 30 Ind.	2.51 (2.69)	-0.78 (-0.66)	0.04 (0.30)	-0.09 (-0.50)	0.48	0.07	0.02	189.12 (0.00)
U-CCAPM	**Inter.**	$\boldsymbol{\triangle c_{0\rightarrow 11}}$						
FF25 + Mkt	0.46 (0.29)	3.83 (0.00)			0.39	0.38	0.02	32.53 (0.11)
FF25 + Mkt + 30 Ind.	1.74 (2.44)	0.17 (0.00)			0.46	-0.01	0.00	185.35 (0.00)
CCAPM	**Inter.**	$\boldsymbol{\triangle c}$						
FF25 + Mkt	2.69 (3.04)	-0.16 (-0.01)			0.50	-0.01	0.01	78.42 (0.00)
FF25 + Mkt + 30 Ind.	2.42 (3.78)	-0.13 (-0.03)			0.43	0.05	0.04	170.68 (0.00)
CAPM	**Inter.**	$\boldsymbol{Mkt}$						
FF25 + Mkt	3.17 (3.20)	-1.00 (0.00)			0.49	0.05	0.03	84.97 (0.00)
FF25 + Mkt + 30 Ind.	2.46 (3.20)	-0.50 (0.00)			0.44	0.02	0.02	188.29 (0.00)
HL	**Inter.**	$\boldsymbol{Mkt}$	$\boldsymbol{\triangle TERM}$	$\boldsymbol{\triangle DEF}$				
FF25 + Mkt	2.30 (1.74)	-0.67 (-0.45)	0.58 (2.51)	0.01 (0.11)	0.28	0.64	0.10	42.96 (0.00)
FF25 + Mkt + 30 Ind.	2.13 (2.55)	-0.32 (-0.30)	0.25 (1.86)	0.02 (0.58)	0.37	0.13	0.03	162.32 (0.00)
FF3	**Inter.**	$\boldsymbol{Mkt}$	$\boldsymbol{SMB}$	$\boldsymbol{HML}$				
FF25 + Mkt	3.40 (3.14)	-1.81 (-1.41)	0.33 (0.77)	1.18 (2.60)	0.24	0.63	0.14	70.27 (0.00)
FF25 + Mkt + 30 Ind.	2.93 (3.69)	-1.26 (-1.25)	0.26 (0.61)	0.83 (1.78)	0.36	0.28	0.07	172.41 (0.00)

Table IX: **Model Comparison Tests (Q1/1969-Q3/2014, 183 Quarters)**

This table presents model comparison tests built on SDF representations and Hansen-Jagannathan (HJ) distances, for several macro-factor models. In Panel A, test assets are the 25 Fama-French size- and book-to-market-sorted portfolios, the 30 Fama-French industry portfolios, and the CRSP value-weighted index. The upper block reports the GMM SDF tests which examine whether factors in other models drive out $\triangle PC2$. The test statistics are Wald statistics based on the efficient GMM outlined in "Model Comparison" in Section 4.3. CC-CAY is the conditional consumption-CAPM by Lettau and Ludvigson (2001), D-CCAPM is the linearized durable consumption-CAPM by Yogo (2006), U-CCAPM is the linearized ultimate consumption-CAPM of Parker and Julliard (2005), CCAPM is the static consumption-CAPM, HL is the intertemporal CAPM of Hahn and Lee (2006), and FF3 is the Fama-French three-factor model. The second block reports Wald statistics, derived from efficient GMM, which examine, in the presence of three risk factors in *Rec*, whether (non-overlapping) factors in other models are driven out. Panel B reports squared sample HJ distances of the macro-factor models and the differences in squared HJ distances between these models and the recession risk model ($\delta^2_{model} - \delta^2_{rec}$), using gross returns on the CRSP value-weighted index and the 25 size and B/M portfolios alone, or in conjunction with 30 industry portfolios. The row labelled "p-value" reports the p-value of the Lagrange multiplier test for the hypothesis $\delta^2 = 0$. The sample is quarterly from 1969Q1 to 2014Q3 (183 quarters) except for D-CCAPM (1969Q1 to 2001Q4) and U-CCAPM (1969Q1 to 2012Q3).

Panel A: GMM SDF Test: $M = 1 - b'[f - \mu_f]$

H0: $b_{\triangle PC2} = 0$	**CCAPM**	**CC-CAY**	**D-CCAPM***	**U-CCAPM**	**HL**	**FF3**
Efficient GMM Wald χ^2_1	4.234	8.335	10.980	7.519	15.390	11.522
p-value	(0.04)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
H0: Rec drive out other factor, $b_{other}=0$						
Efficient GMM Wald χ^2_1	0.188	46.968	28.080	0.202	20.020	22.050
p-value	(0.66)	(0.00)	(0.00)	(0.65)	(0.00)	(0.00)

Panel B: Hansen-Jagannathan Distance Tests

	CCAPM	**CC-CAY**	**D-CCAPM***	**U-CCAPM**	**HL**	**FF3**	**Rec**
FF25 + Mkt							
δ^2	0.447	0.442	0.567	0.457	0.400	0.378	0.375
p-value ($\delta^2 = 0$)	(0.00)	(0.00)	(0.00)	(0.00)	(0.40)	(0.00)	(0.01)
$\delta^2_{model} - \delta^2_{rec}$	0.072	0.067	0.192	0.082	0.025	0.002	0.000
FF25 + 30 Ind + Mkt							
δ^2	0.934	0.941	1.414	0.981	0.937	0.897	0.920
p-value ($\delta^2 = 0$)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
$\delta^2_{model} - \delta^2_{rec}$	0.015	0.021	0.494	0.061	0.017	-0.023	0.000

Table X: **Time Series Regressions of Quarterly Excess Returns on the Fama-French 25 Size- and Book-to-market-sorted Portfolios on the Recession Risk Model (Q1/1969-Q4/2014, 184 Quarters)**

This table shows time series regressions of quarterly excess returns of the 25 Fama-French size- and book-to-market-sorted portfolios on the recession risk model.

$$R^e_{i,t} = a_i + \beta^i_{Mkt} Mkt_t + \beta^i_{\triangle PC1} \triangle PC1_t + \beta^i_{\triangle PC2} \triangle PC2_t + \epsilon^i_t$$

where i indexes assets, Mkt_t, $\triangle PC1_t$ and $\triangle PC2_t$ denote excess return on the CRSP value-weighted index, and the innovations to $PC1$ and $PC2$, respectively. $PC1$ and $PC2$ are the first (level) and the second principal components (slope) of the term structure of SPF recession probabilities (in percentage terms). The innovations to $PC1$ and $PC2$ are estimated by a first-order VAR of $PC1$ and $PC2$ over the entire sample. β^i_{Mkt}, $\beta^i_{\triangle PC1}$ and $\beta^i_{\triangle PC2}$ are unconditional factor exposures of the excess return of asset i, $R^e_{i,t}$, on Mkt_t, $\triangle PC1_t$ and $\triangle PC2_t$. $E[R^e]$ refers to average excess return (actual return in excess of return on the 3 month T-bill) and R^2 is the (unadjusted) R-squares. t-statistics of factor exposures are adjusted by the Newey-West approach and the Bartlett kernel with 1 lag. χ^2_{25} refers to a large sample likelihood-ratio test for the null hypothesis that all the 25 assets' factor exposures of a risk factor are jointly zero. The sample is quarterly from 1969Q1 to 2014Q4 (184 quarters). The data for the one-month T-bill and the 25 Fama-French size- and book-to-market-sorted portfolios are from Kenneth French's web site. Returns and risk premia are reported in percentage terms per quarter.

	Size/Book-to-Market Equity					Size/Book-to-Market Equity					
	Low	2	3	4	High	Low	2	3	4	High	
	Panel A $E[R^e]$ (%)					Panel B Time Series R^2					
Small	0.41	2.18	2.30	2.84	3.23	0.74	0.75	0.73	0.71	0.68	
2	1.33	2.10	2.58	2.70	2.86	0.82	0.80	0.80	0.75	0.69	
3	1.49	2.27	2.24	2.49	3.12	0.85	0.86	0.80	0.76	0.66	
4	1.91	1.76	2.16	2.36	2.48	0.87	0.86	0.83	0.80	0.72	
Big	1.46	1.78	1.49	1.64	1.88	0.89	0.89	0.80	0.76	0.66	
	Panel C β_{Mkt}					Panel D $t(\beta_{Mkt})$					$\chi^2_{25}(\beta_{Mkt} = 0)$
Small	1.56	1.29	1.12	1.03	1.13	19.44	17.50	16.34	15.89	14.00	> 100
2	1.48	1.22	1.07	1.02	1.07	24.44	20.41	18.79	16.83	14.48	p-value
3	1.40	1.15	1.00	0.96	0.99	29.87	25.84	18.49	16.35	13.61	0
4	1.29	1.10	0.99	0.95	1.02	32.06	25.02	20.61	18.99	15.05	
Big	1.01	0.91	0.81	0.79	0.83	35.33	31.69	23.02	18.31	15.92	
	Panel E $\beta_{\triangle PC1}$					Panel F $t(\beta_{\triangle PC1})$					$\chi^2_{25}(\beta_{\triangle PC1} = 0)$
Small	-0.03	-0.04	-0.07	-0.06	-0.09	-0.66	-1.05	-1.91	-1.91	-2.33	80.57
2	0.03	0.00	-0.03	-0.01	-0.04	0.90	-0.03	-0.94	-0.30	-1.02	p-value
3	0.05	0.00	0.00	-0.02	0.02	1.84	0.09	-0.16	-0.68	0.54	0
4	0.04	0.01	-0.02	0.00	-0.03	2.39	0.83	-0.90	0.12	-0.95	
Big	0.02	-0.01	-0.03	-0.02	-0.01	1.60	-0.45	-1.57	-1.15	-0.48	
	Panel G $\beta_{\triangle PC2}$					Panel H $t(\beta_{\triangle PC2})$					$\chi^2_{25}(\beta_{\triangle PC2} = 0)$
Small	-0.14	-0.21	-0.20	-0.24	-0.33	-1.34	-2.47	-2.42	-3.15	-3.69	74.46
2	-0.04	-0.11	-0.13	-0.15	-0.22	-0.59	-1.49	-2.20	-2.67	-2.73	p-value
3	0.02	-0.09	-0.09	-0.15	-0.12	0.25	-2.14	-1.99	-3.44	-1.61	0
4	0.06	-0.02	-0.11	-0.13	-0.09	1.31	-0.56	-2.91	-3.25	-1.34	
Big	0.07	0.02	0.03	-0.04	-0.09	2.23	0.73	0.89	-1.29	-1.48	

Table XI: **Forecasting the Cumulative Profitability Changes on 5 Book-to-Market-Sorted Portfolios (1969-2013, 45 Years)**

This table reports ordinary least square (OLS) estimates, t-statistics (in parentheses), and adjusted OLS $\bar{R}^2s$ of predictive regressions of annualized cumulative changes in the portfolio-level profitability of five book-to-market-sorted portfolios on $PC1$ and $PC2$. $PC1$ and $PC2$ are the first (Level) and second (Slope) principal components of the term structure of SPF recession probabilities (in percentage terms). Firm-level profitability is measured by ROA, defined as current year operating income before depreciation (Compustat item: OIBDP) divided by average total assets (Compustat item: AT) of the current year and previous year. Portfolio-level profitability is the value-weighted ROA of individual firms within each portfolio. The specification of predictive regressions is as follows,

$$\overline{\triangle \text{Profit}}^i_{t-1\to t+h-1} = \alpha^i(h) + b1^i(h)PC1_t + b2^i(h)PC2_t + \epsilon^i_{t,h}$$

where time t is measured annually, $\overline{\triangle \text{Profit}}^i_{t-1\to t+h-1} \equiv \frac{100}{h}(\text{Profit}^i_{t+h-1} - \text{Profit}^i_{t-1})$ is annualized cumulative changes in the profitability of portfolio i from year $t-1$ to year $t+h-1$, and the forecasting horizon h takes the values 2, 3, and 4. The five book-to-market-sorted portfolios are constructed in the manner of Fama and French (1992). L, M, and H denote three different portfolios, consisting of stocks in the first, third, and fifth book-to-market quintile. t-statistics (in parentheses) are adjusted using the Hodrick (1992) standard errors. The data is annually from 1969 to 2013, 45 years in total. Firm-level accounting data are from Compustat.

Annualized Cumulative Changes in Portfolio-Level ROA									
	$\overline{\triangle \text{Profit}}_{t-1\to t+1}$			$\overline{\triangle \text{Profit}}_{t-1\to t+2}$			$\overline{\triangle \text{Profit}}_{t-1\to t+3}$		
B/M quintile	L	M	H	L	M	H	L	M	H
$PC1_t$	-0.010	-0.021	-0.009	-0.004	-0.016	-0.004	-0.003	-0.011	0.000
t-stat	-(2.31)	-(5.82)	-(2.30)	-(1.20)	-(4.73)	-(1.23)	-(1.27)	-(3.86)	-(0.20)
$PC2_t$	-0.011	-0.014	-0.021	-0.017	-0.027	-0.029	-0.017	-0.026	-0.022
t-stat	-(1.02)	-(1.96)	-(1.66)	-(1.87)	-(3.80)	-(2.75)	-(2.54)	-(3.73)	-(2.79)
$\bar{R}^2$	0.05	0.23	0.18	0.02	0.38	0.29	0.06	0.35	0.26
Obs	45	45	45	44	44	44	43	43	43

Table XII: **Fama-MacBeth Regressions of Quarterly Excess Stock Returns on Historical Factor Exposures and Firm-level Characteristics (Q1/1974-Q4/2014, 164 Quarters)**

This table presents results of stock-level Fama-MacBeth cross-sectional regressions of quarterly excess stock returns on historical factor exposures and firm-level characteristics,

$$R^e_{i,t+1} = \beta^i_{Mkt,t}\lambda^{Mkt}_{t+1} + \beta^i_{\triangle PC1,t}\lambda^{\triangle PC1}_{t+1} + \beta^i_{\triangle PC2,t}\lambda^{\triangle PC2}_{t+1} + X_{i,t}\gamma_{t+1} + \epsilon^i_{t+1},\ t = 1, ..., T$$

where $R^e_{i,t+1}$ is the quarter-$t+1$ excess return on asset i, $\beta^i_{Mkt,t}$, $\beta^i_{\triangle PC1,t}$ and $\beta^i_{\triangle PC2,t}$ are quarter-t factor exposures on market excess return, $\triangle PC1$, and $\triangle PC2$, estimated by rolling window time series regressions of past 20 quarter data up to quarter-t. $X_{i,t}$ are firm-level characteristics, including the logarithm of market equity (log(ME)), the logarithm of book-to-market equity ratio (log(B/M)), past 12 month to 2 month cumulative returns ($r_{2,12}$), gross profitability (GP), and asset growth (I/A). The time series averages of the quarter-by-quarter cross-sectional regression coefficients and associated t-statistics (t-FM) are reported. t-statistics are adjusted by Newey-West standard errors with 1 lag. Panel A reports results of all common stocks from the CRSP and Panel B reports results of stocks in NYSE only. The sample is quarterly from 1974Q1 to 2014Q4 (164 quarters). Returns and risk premia are reported in percentage terms per quarter.

	Panel A: All CRSP stocks					**Panel B: NYSE stocks**				
	I	II	III	IV	V	I	II	III	IV	V
Mkt	1.75	1.52	1.65	1.09	0.88	1.85	1.77	1.78	0.78	0.57
t-FM	(3.13)	(2.90)	(2.98)	(2.51)	(2.20)	(3.01)	(3.04)	(2.92)	(1.63)	(1.28)
$\triangle PC1$	-1.88		-1.29	-0.78	-0.67	-1.84		-1.00	-0.14	-0.09
t-FM	-(2.52)		-(1.71)	-(1.38)	-(1.24)	-(2.11)		-(1.14)	-(0.21)	-(0.14)
$\triangle PC2$		-0.89	-0.99	-0.79	-0.61		-0.70	-0.83	-0.74	-0.60
t-FM		-(3.11)	-(3.31)	-(3.20)	-(2.75)		-(2.26)	-(2.64)	-(2.65)	-(2.36)
log(ME)				0.23	0.10				0.17	0.11
t-FM				(2.86)	(1.38)				(2.56)	(1.63)
log(B/M)				1.23	1.25				0.76	1.00
t-FM				(5.58)	(5.70)				(3.07)	(3.69)
$r_{2,12}$				0.61	0.57				0.82	0.82
t-FM				(1.16)	(1.09)				(1.10)	(1.12)
GP					3.26					2.48
t-FM					(6.61)					(4.20)
I/A					-0.94					-0.60
t-FM					-(5.53)					-(1.90)

Table XIII: **Quarterly Excess Returns on Factor Mimicking Portfolios (Q1/1969-Q4/2014, 184 Quarters)**

This table presents summary statistics of factor mimicking portfolios (FMPs) of $\triangle PC1$ and $\triangle PC2$ ($\triangle PC1$ **FMP** and $\triangle PC2$ **FMP**, respectively). $PC1$ and $PC2$ are the first and second principal components of the term structure of SPF recession probability forecasts. $\triangle PC1_t$ and $\triangle PC2_t$ are the innovations to $PC1$ and $PC2$, respectively, estimated by a VAR(1) model of $PC1$ and $PC2$ using the whole sample. The two FMPs are created by projecting $\triangle PC1$ and $\triangle PC2$ into a space of basis assets as follows,

$$y_t = a + b^{'} X_t + \epsilon_t, \; y_t \in \{\triangle PC1_t, \triangle PC2_t\}$$

where b is estimated by ordinary least squares and the FMPs are given by $b^{'} X_t$. The space of basis assets is $X_t = [BL, BM, BH, SL, SM, SH, b1, b4, b5, corpr]$ where the first six variables denote excess returns on the six Fama-French size- and book-to-market-sorted portfolios. $b1$, $b4$, and $b5$ refer to excess returns on the three Fama bond portfolios sorted by maturity, which comprise U.S. T-bills or T-Notes with maturities of 0-1, 3-4, and 4-5 years, respectively, and *corpr* is the excess return on the Ibboston long-term corporate bond portfolio, which comprises investment-grade corporate bonds with maturity greater than 10 years. Panel A reports the quarterly means, standard deviations and annualized Sharpe ratios (SR) of the two FMPs and the Fama-French three factors. Panel B reports the correlation between the two FMPs and the Fama-French three factors. Panel C reports the time series regressions of $\triangle PC2$ **FMP** on the CAPM and the Fama-French three factors. Panel D reports GRS F-statistics with associated p-values for four models, CAPM, the Fama-French three-factor model, market with $\triangle PC2$ **FMP**, denoted MKT+$\triangle PC2\ FMP$, and market with $\triangle PC1$ **FMP** and $\triangle PC2$ **FMP**, denoted "Rec FMP". The sample is quarterly from 1969Q1 to 2014Q4 (184 quarters). Returns and risk premia are reported in percentage terms per quarter. $t-$statistics are adjusted by Newey-West standard errors with 1 lag.

Panel A: Sample Moments (%)

	Mean	t-stat	Std	Annualized SR
$\triangle PC1$ **FMP**	0.29	(0.54)	7.15	0.08
$\triangle PC2$ **FMP**	-0.77	-(4.04)	2.58	-0.59
Mkt	1.54	(2.35)	8.92	0.35
SMB	0.53	(1.28)	5.62	0.19
HML	1.06	(2.39)	6.03	0.35

Panel B: Correlation Matrix

	$\triangle PC1$ **FMP**	Mkt	SMB	HML
$\triangle PC2$ **FMP**	0.27	-0.41	-0.67	-0.29
p-value	(0.00)	(0.00)	(0.00)	(0.00)
Mkt	-0.48		0.46	-0.34
p-value	(0.00)		(0.00)	(0.00)
SMB	-0.26			-0.11
p-value	(0.00)			(0.13)
HML	-0.04			
p-value	(0.57)			

Panel C: CAPM and FF3 α (%)

$\triangle PC2$ **FMP**	α	β_{Mkt}	β_{SMB}	β_{HML}	$\bar{R}^2$
CAPM	-0.59	-0.12			0.16
	-(3.29)	-(5.35)			
FF3	-0.29	-0.08	-0.27	-0.20	0.64
	-(2.18)	-(4.80)	-(12.56)	-(8.85)	

Panel D: Pricing FF25 Size-B/M sorted portfolios

	CAPM	FF3	MKT+$\triangle PC2\ FMP$	Rec FMP
GRS F-stat	3.80	3.19	3.22	3.21
p-value	0.00	0.00	0.00	0.00

Table XIV: **Pricing Monthly Excess Returns on the Fama-French 25 Size- and Book-to-market-sorted Portfolios and the 10 Industry Portfolios (7/1963-12/2014, 618 Months)**

This table presents cross-sectional regressions of average excess returns on the Fama-French 25 size- and book-to-market-sorted portfolios and the 10 industry portfolios on their unconditional factor exposures. The sample is monthly from July 1963 to December 2014, 618 months in total. Each model is estimated by a cross-sectional regression $E_T[R^e_{i,t}] = \alpha + \beta^i_{fac}\lambda_{fac} + \xi_i,\ i = 1, ..., N$ where $E_T[R^e_{i,t}]$ is the average excess return on asset i, α is the excess zero-beta rate, and ξ_i is the cross-sectional pricing error of asset i. β^i_{fac} and λ_{fac} represent the factor exposures of asset i and factor risk premia, respectively. CAPM is the Capital Asset Pricing Model, FF3 denotes the Fama-French three-factor model, Rec FMP stands for the factor mimicking portfolios of the recession risk model (Mkt, $\triangle PC1$ FMP, $\triangle PC2$ FMP), and MKT+$\triangle PC2$ FMP is a two-factor specification of the recession risk model. See Table XIII for the description of the factor mimicking portfolios. Panel A reports estimated prices of risk with Fama-MacBeth and GMM-type t-statistics that correct the error-in-variable problem for estimated βs. Panel B displays diagnostic statistics, including mean absolute pricing errors (MAPEs, $\frac{1}{N}\sum|\xi_i|$), adjusted OLS and GLS cross-sectional R-squares, Hansen's over-identification J_T statistics, which gauge the joint significance of ξ_i, and GRS F-statistics for the joint significance of the intercepts in time series regressions. The J_T statistics follow χ^2 distributions with p-values shown in the row labeled "J_T p-value". "GRS p-value" are the p-values of the GRS statistics. Risk premia are reported in percentage terms per quarter.

Panel A: Prices of Risk

	CAPM	**FF3**	**Rec FMP**	**MKT+$\triangle PC2$ FMP**
Intercept	2.15	2.56	2.91	3.14
t-FM	(2.62)	(3.87)	(4.47)	(3.91)
t-GMM	(2.62)	(3.83)	(4.36)	(3.81)
Mkt	-0.10	-0.92	-1.32	-1.52
t-FM	-(0.09)	-(1.08)	-(1.56)	-(1.59)
t-GMM	(0.00)	-(1.07)	-(1.54)	-(1.57)
SMB		0.57		
t-FM		(1.49)		
t-GMM		(1.49)		
HML		0.92		
t-FM		(2.56)		
t-GMM		(2.56)		
$\triangle PC1$ FMP			-0.24	
t-FM			-(0.26)	
t-GMM			-(0.25)	
$\triangle PC2$ FMP			-0.58	-0.59
t-FM			-(2.41)	-(2.50)
t-GMM			-(2.38)	-(2.48)

Panel B: Test Diagnostics

	CAPM	**FF3**	**Rec FMP**	**MKT+$\triangle PC2$ FMP**
MAPE	0.50	0.30	0.27	0.27
$\bar{R}^2_{OLS}$	-0.03	0.51	0.57	0.57
R^2_{GLS}	0.06	0.19	0.24	0.23
Over-identification J_T	120.17	101.13	92.15	94.35
J_T p-value	0.00	0.00	0.00	0.00
GRS F-test	4.71	4.03	4.37	4.20
GRS p-value	0.00	0.00	0.00	0.00

Table XV: **Pricing Monthly Excess Returns on the SPX Index Options Portfolios and the Fama-French 25 Size- and Book-to-market-sorted Portfolios (4/1986-1/2012, 310 Months)**

This table presents cross-sectional regressions of average excess returns on the 18 S&P 500 Index option portfolios and the 25 size- and book-to-market-sorted portfolios on their unconditional factor exposures. The 18 option portfolios comprise an equal number of European call and put options with maturities of 30 days, 60 days, and 90 days and spot-to-strike ratios of 0.9, 1, and 1.1, respectively. The sample is monthly from April 1986 to January 2012, 310 months in total. Each model is estimated via a cross-sectional regression $E_T[R^e_{i,t}] = \alpha + \beta^i_{fac}\lambda_{fac} + \xi_i,\ i = 1, ..., N$ where $E_T[R^e_{i,t}]$ is the average excess return on asset i, α is the excess zero-beta rate, and ξ_i is the cross-sectional pricing error. β^i_{fac} and λ_{fac} represent the factor exposures of asset i and factor risk premia, respectively. DCAPM is the downside CAPM (Mkt, $MktDR$), FF3 denotes the Fama-French three-factor model (Mkt, SMB, HML), and Rec FMP stands for the factor mimicking portfolios of the recession risk model (Mkt, $\triangle PC1$ FMP, $\triangle PC2$ FMP). See Table XIII for the description of the factor mimicking portfolio. Panel A reports estimated prices of risk with Fama-MacBeth and GMM t-statistics. Panel B displays diagnostic statistics, including mean absolute pricing errors (MAPEs, defined as $\frac{1}{N}\sum|\xi_i|$), adjusted cross-sectional OLS $\bar{R}^2$ and Hansen's over-identification J_T statistics, which gauge the joint significance of ξ_i. The J_T statistics follow χ^2 distributions with p-value shown in the row labeled J_T p-value. The data for the S&P 500 Index option portfolios are from Constantinides, Jackwerth and Savov (2013). The data for the one-month T-bill and the 25 size- and book-to-market-sorted portfolios are from Kenneth French's web site. Risk premia are reported in percentage terms per quarter.

	Panel A: Prices of Risk					
	SPX Options			SPX Options + Equities		
	DCAPM	**Rec FMP**	**FF3**	**DCAPM**	**Rec FMP**	**FF3**
Intercept				2.00	**-3.00**	**-4.18**
t-FM				(1.54)	-(2.80)	-(3.54)
t-GMM				-	-(2.58)	-(3.20)
Mkt	**2.11**	**1.65**	**2.69**	-0.50	**4.53**	**5.78**
t-FM	(2.47)	(1.96)	(3.31)	-(0.32)	(3.32)	(3.93)
t-GMM	-	(1.91)	(3.25)	-	(3.13)	(3.64)
MktDR	**4.63**			**4.19**		
t-FM	(4.88)			(5.12)		
t-GMM	-			-		
SMB			**8.24**			0.23
t-FM			(6.15)			(0.39)
t-GMM			(4.89)			(0.39)
HML			-1.23			0.95
t-FM			-(0.38)			(1.68)
t-GMM			-(0.29)			(1.66)
$\triangle PC1$ **FMP**		-0.12			**-3.86**	
t-FM		-(0.06)			-(4.06)	
t-GMM		-(0.04)			-(3.82)	
$\triangle PC2$ **FMP**		**-2.83**			**-0.81**	
t-FM		-(4.53)			-(2.57)	
t-GMM		-(3.72)			-(2.47)	

	Panel B: Test Diagnostics					
	DCAPM	**Rec FMP**	**FF3**	**DCAPM**	**Rec FMP**	**FF3**
MAPE	0.38	0.32	0.38	0.50	0.56	0.55
$\bar{R}^2$	0.88	0.89	0.85	0.63	0.49	0.50
Over-identification J_T	169.70	99.47	94.97	289.10	240.54	236.57
J_T p-value	0.00	0.00	0.00	0.00	0.00	0.00

Table XVI: **Pricing Monthly Excess Returns on the Five Currency Portfolios and the Fama-French 25 Size- and Book-to-market-sorted Portfolios (1/1974-3/2010, 435 Months)**

This table presents cross-sectional regressions of average excess returns on the 5 currency portfolios and the 25 size- and book-to-market-sorted portfolios on their unconditional factor exposures. The 5 currency portfolios are nominal-interest-rate-sorted currency portfolios, which comprise currencies of developed countries. Each currency portfolio is a zero-cost portfolio that takes long positions in currencies of developed countries other than the U.S., while funding the positions by borrowing U.S. dollars. The sample is monthly from January 1974 to March 2010, 435 months in total. Each model is estimated via a cross-sectional regression $E_T[R^e_{i,t}] = \alpha + \beta^i_{fac}\lambda_{fac} + \xi_i,\ i = 1, ..., N$, where $E_T[R^e_{i,t}]$ is the average excess return on asset i, α is the excess zero-beta rate, and ξ_i is the cross-sectional pricing error of asset i. β^i_{fac} and λ_{fac} represent the factor exposures of asset i and factor risk premia, respectively. DCAPM is the downside CAPM (Mkt, $MktDR$), FF3 denotes the Fama-French three-factor model (Mkt, SMB, HML), and Rec FMP stands for the factor mimicking portfolio of the macroeconomic recession risk model (Mkt, $\triangle PC1$ FMP, $\triangle PC2$ FMP). See Table XIII for the description of the factor mimicking portfolio. Panel A reports estimated prices of risk with Fama-MacBeth and GMM t-statistics. Panel B displays diagnostic statistics, including mean absolute pricing errors (MAPEs, defined as $\frac{1}{N}\sum|\xi_i|$), adjusted cross-sectional $\bar{R}^2$, and Hansen's over-identification J_T statistics, which gauge the joint significance of ξ_i. The J_T statistics follow χ^2 distributions with p-value shown in the row labeled J_T p-value. The data for the 5 currency portfolios are from Lettau, Maggiori, and Weber (2014). The data for the one-month T-bill and the 25 size- and book-to-market-sorted portfolios are from Kenneth French's web site. Risk premia are reported in percentage terms per quarter.

	Panel A: Prices of Risk					
	Currencies			Currencies + Equities		
	DCAPM	**Rec FMP**	**FF3**	**DCAPM**	**Rec FMP**	**FF3**
Intercept				0.44	**0.91**	0.42
t-FM				(1.25)	(2.51)	(1.26)
t-GMM				-	(2.31)	(1.23)
Mkt	**1.55**	**1.59**	**1.60**	0.98	0.45	1.04
t-FM	(2.30)	(2.36)	(2.38)	(1.27)	(0.59)	(1.38)
t-GMM	-	(2.36)	(2.38)	-	(0.58)	(1.38)
MktDR	**7.38**			4.81		
t-FM	(2.54)			(4.33)		
t-GMM	-			-		
SMB			-4.54			0.78
t-FM			-(0.71)			(1.67)
t-GMM			-(0.59)			(1.67)
HML			3.62			**1.45**
t-FM			(1.40)			(3.15)
t-GMM			(1.18)			(3.15)
$\triangle PC1$ **FMP**		2.64			**-3.91**	
t-FM		(1.05)			-(2.59)	
t-GMM		(0.81)			-(2.40)	
$\triangle PC2$ **FMP**		**-3.07**			**-0.85**	
t-FM		-(3.15)			-(3.01)	
t-GMM		-(2.44)			-(2.89)	

	Panel B: Test Diagnostics					
	DCAPM	**Rec FMP**	**FF3**	**DCAPM**	**Rec FMP**	**FF3**
MAPE	0.20	0.33	0.40	0.40	0.32	0.33
$\bar{R}^2$	0.85	0.60	0.50	0.70	0.81	0.79
Over-identification J_T	11.44	9.21	13.31	108.30	85.68	107.43
J_T p-value	0.02	0.03	0.00	0.00	0.00	0.00

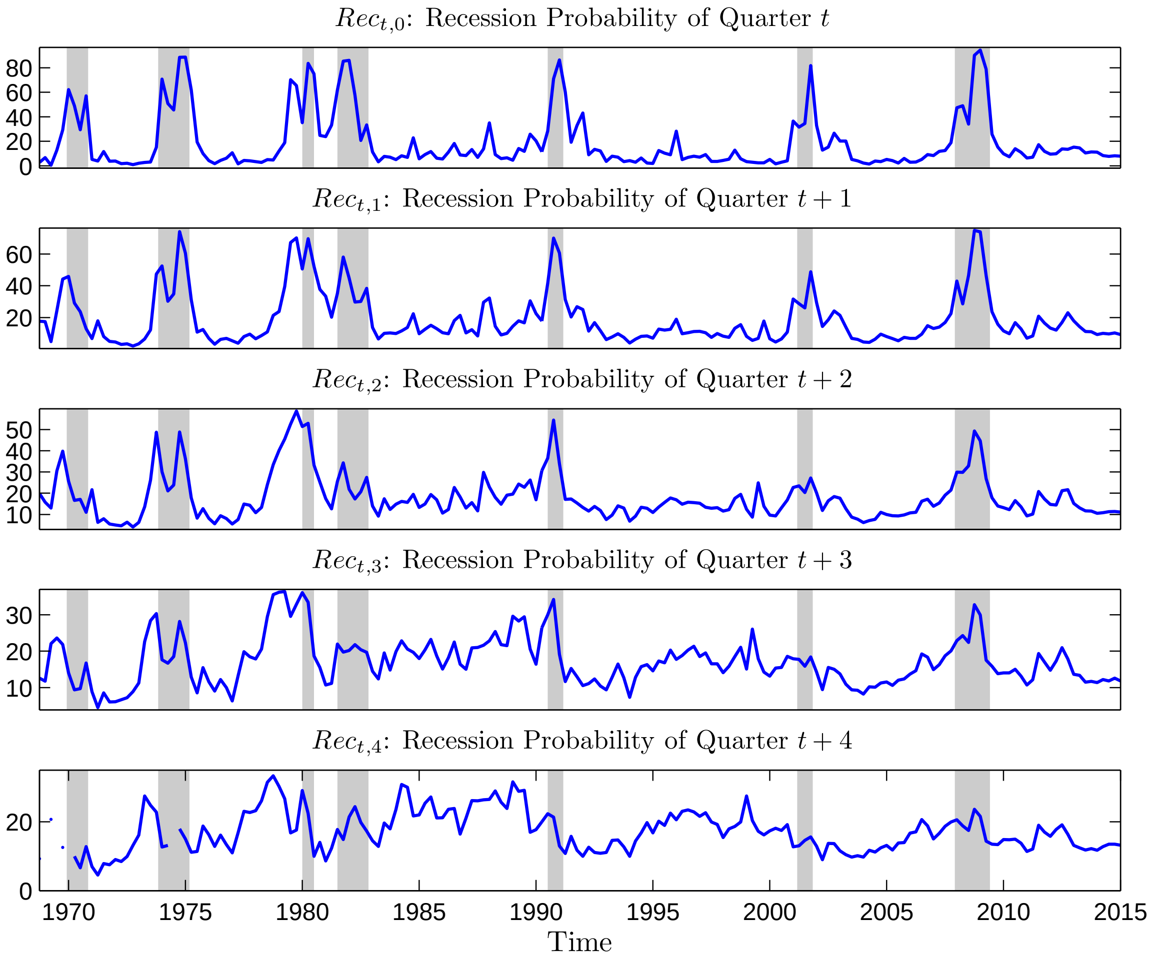

Figure 1: **SPF Recession Probabilities (%)**

Figure 1 plots the time series of recession probability forecasts from the Survey of Professional Forecasters (SPF) database. A recession probability forecast for quarter-$t+i$ made at quarter-t, denoted $Rec_{t,i}$, is the probability of a decline in U.S. real gross domestic product (GDP) in quarter-$t+i$. Mathematically, $Rec_{t,i}$ is defined as $Rec_{t,i} \equiv Pr_t(GDP_{t+i} < GDP_{t+i-1}), i \in \{0, 1, ..., 4\}$ where time t is measured in quarters and GDP_{t+i} refers to the level of real GDP in quarter-$t+i$. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters.

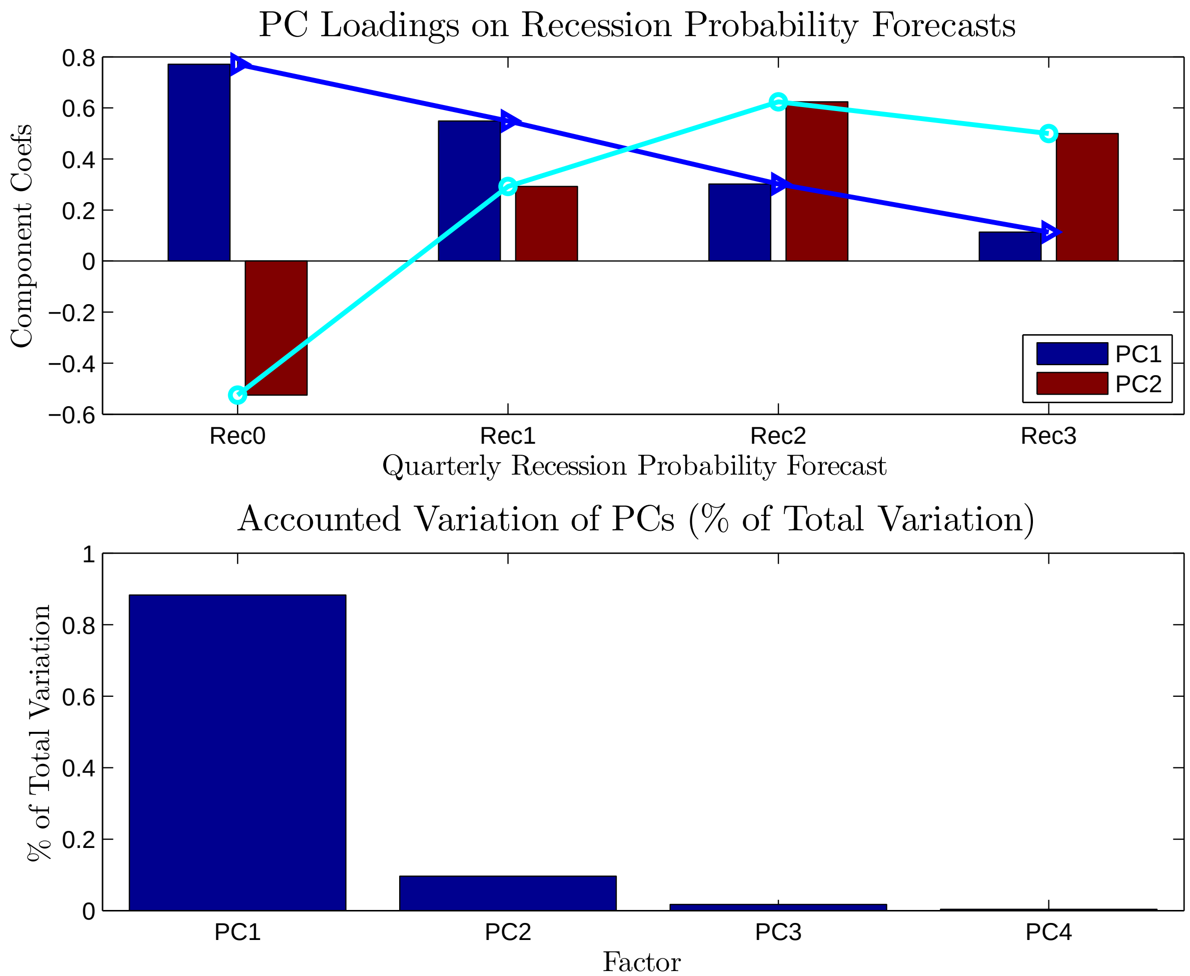

Figure 2: **Principal Components of the Term Structure of SPF Recession Probabilities**

Panel A of Figure 2 plots the loadings of the first two principal components of the term structure of recession probabilities on each individual recession probability. Panel B displays the proportion of the variation of the term structure accounted for by each principal component. A recession probability forecast of quarter-$t+i$ made at quarter-t is denoted $Rec_{t,i}$ and is the probability of a decline in U.S. real gross domestic product (GDP) in quarter-$t+i$. Mathematically, $Rec_{t,i}$ is defined as $Rec_{t,i} \equiv Pr_t(GDP_{t+i} < GDP_{t+i-1}), i \in \{0, 1, ..., 3\}$ where the time t is measured in quarters and GDP_{t+i} refers to the level of real GDP in quarter-$t+i$. The data are from the Survey of Professional Forecasters (SPF) database. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters.

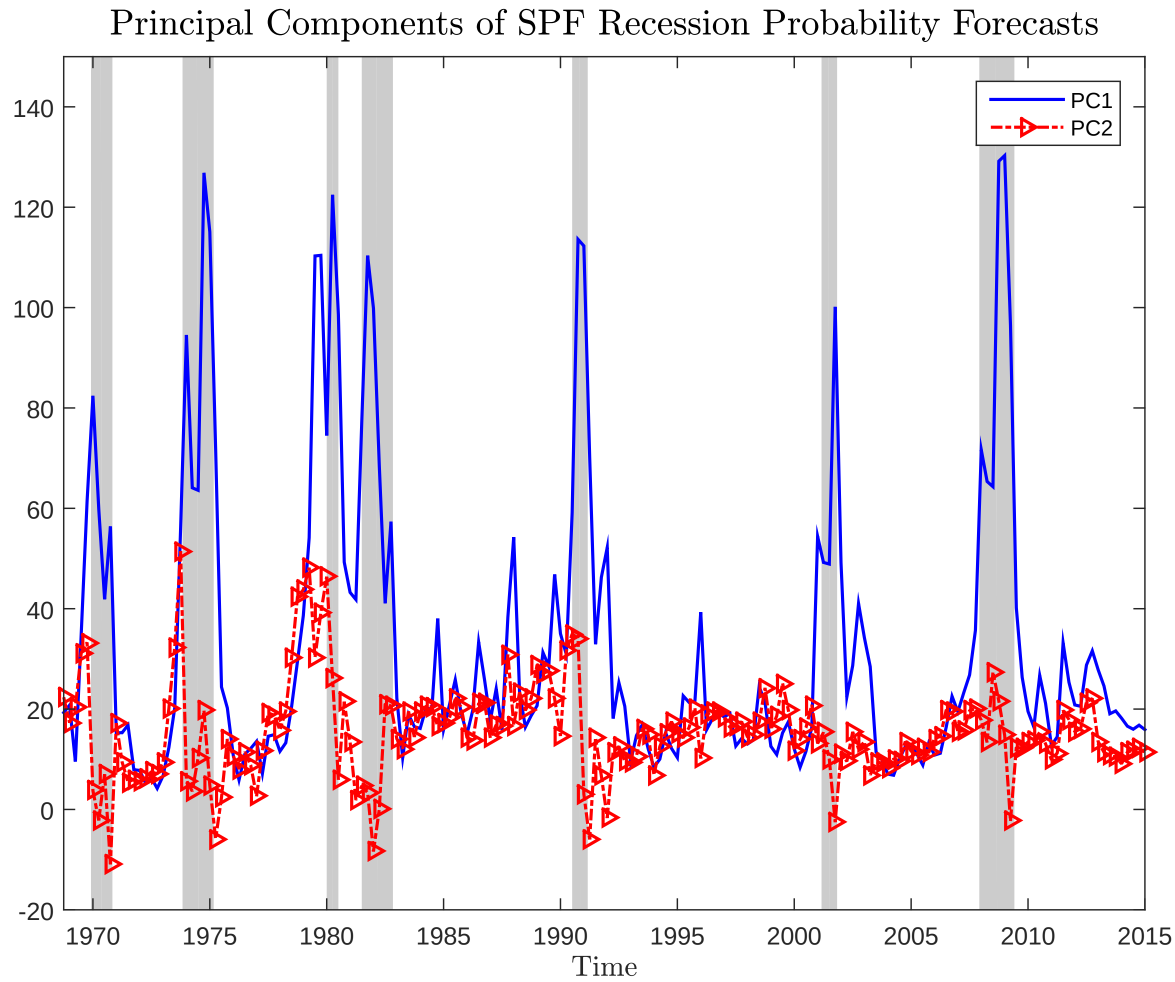

Figure 3: **Principal Components of the SPF Recession Probabilities**

Figure 3 plots the time series of the first ($PC1$) and the second ($PC2$) principal components of the term structure of recession probabilities. The recession probability forecasts are the probabilities of a decline in U.S. real gross domestic product (GDP) in the current quarter and the next three quarters. The solid blue line is the time series of $PC1$ and the dashed red line is the time series of $PC2$. The data on recession probabilities are from the Survey of Professional Forecasters (SPF) database. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters.

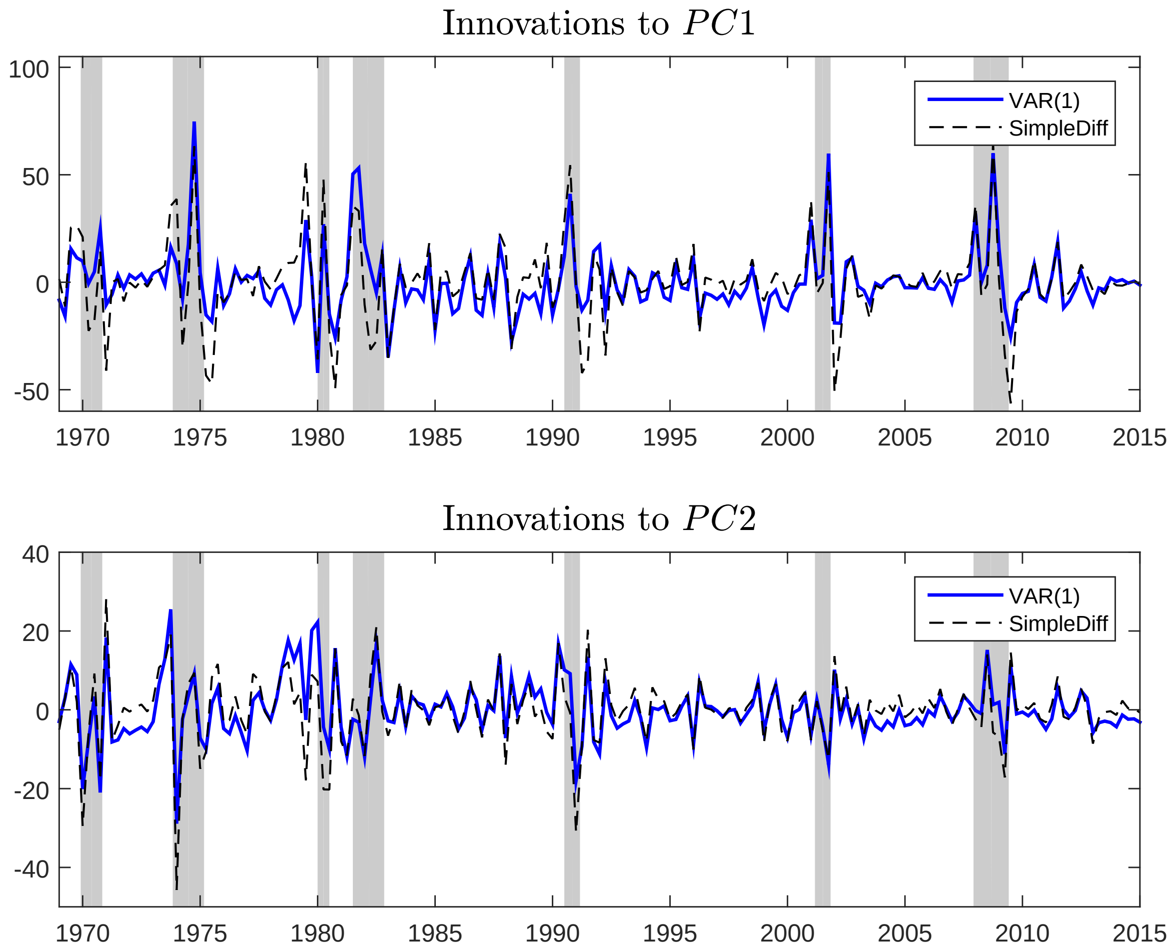

Figure 4: **Innovations to the Principal Components of the SPF Recession Probabilities**

Figure 4 plots the innovations to the first ($PC1$) and the second ($PC2$) principal components of the term structure of recession probabilities. The solid blue line is the innovation estimated by a first-order VAR and the dashed black line is the innovation estimated by simple first difference. The data of recession probabilities are from the Survey of Professional Forecasters (SPF) database. The sample is quarterly from the fourth quarter of 1968 (1968Q4) to the first quarter of 2015 (2015Q1), 186 quarters.

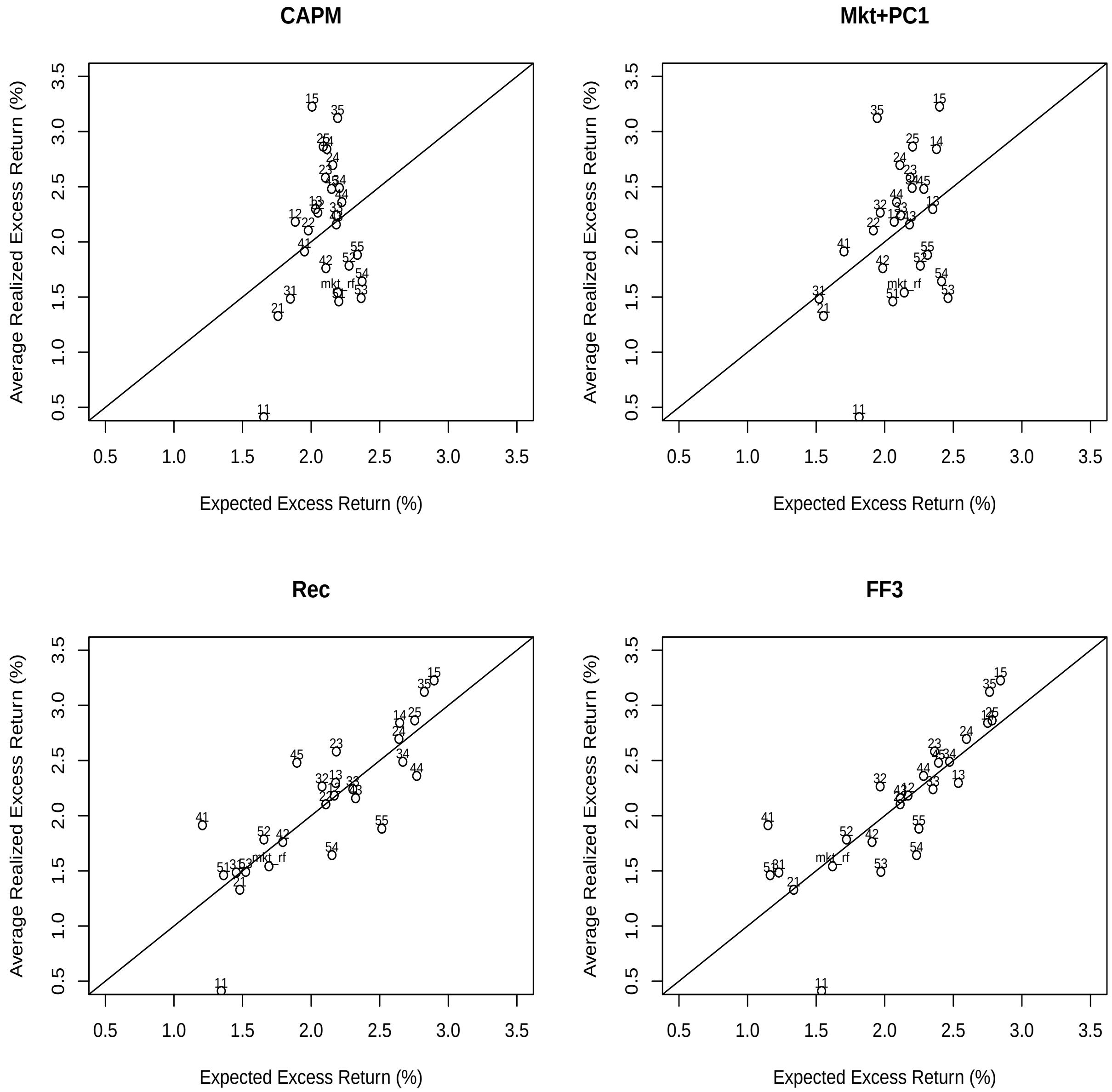

Figure 5: **Pricing Quarterly Excess Returns on the Fama-French 25 Size- and Book-to-market-sorted Portfolios, Q1/1969-Q4/2014, 184 Quarters**

Figure 5 plots average quarterly excess returns on 26 equity portfolios (the 25 Fama-French size- and book-to-market-sorted portfolios (labeled 11-55), and the CRSP value-weighted index (labeled Mkt_rf)) against the mean excess returns predicted by four models. Each model is estimated by a cross-sectional regression $E_T[R^e_t] = \alpha\mathbf{1} + \beta'_{fac}\lambda_{fac} + \xi$ where $E_T[R^e_t]$ is the vector of the average excess returns, α is the excess zero-beta rate, and ξ is the vector of pricing errors. The predicted mean excess returns are $\alpha\mathbf{1} + \beta'_{fac}\lambda_{fac}$. CAPM stands for the Capital Asset Pricing Model, FF3 denotes the Fama-French three-factor model, Rec refers to the recession risk model, and Mkt+PC1 is a two-factor model with the market and the innovation to $PC1$. The sample is quarterly from 1969Q1 to 2014Q4.

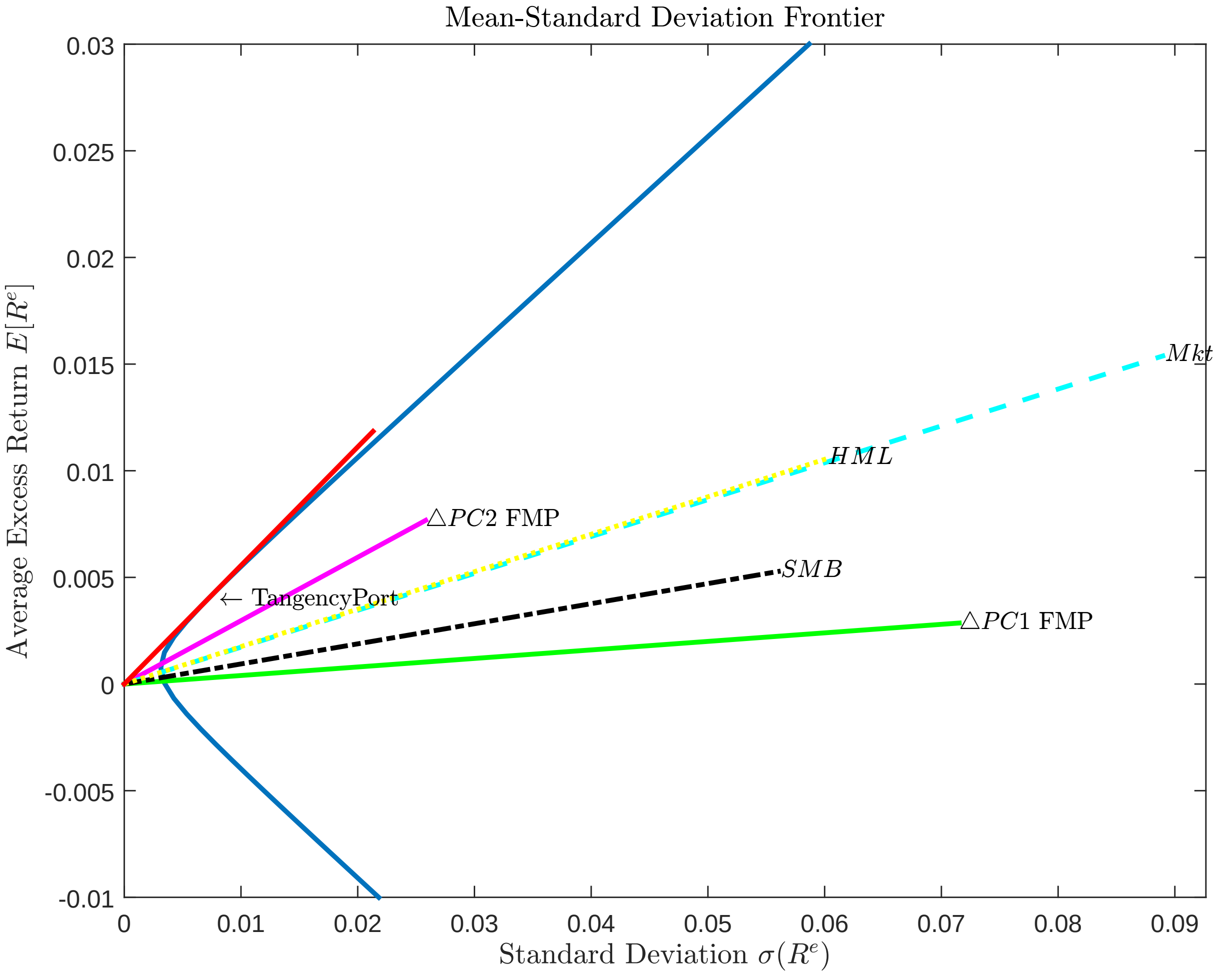

Figure 6: **Mean-Standard Deviation Frontier of Basis Assets**

Figure 6 plots the mean-standard deviation frontier, using the quarterly excess returns on the 10 basis assets for constructing the factor mimicking portfolios of the first ($PC1$) and the second ($PC2$) principal components of the term structure of recession probabilities. The space of basis assets is $[BL, BM, BH, SL, SM, SH, b1, b4, b5, corpr]$ where the first six variables denote excess returns on the six Fama-French size- and book-to-market-sorted portfolios. $b1$, $b4$, and $b5$ refer to excess returns on the three Fama bond portfolios sorted by maturity, which comprise U.S. T-bills or T-Notes with maturities of 0-1, 3-4, and 4-5 years, respectively, and $corpr$ is the excess return on the Ibboston long-term corporate bond portfolio, which comprises investment-grade corporate bonds with maturity greater than 10 years. $\triangle PC1$ FMP and $\triangle PC2$ FMP are the two factor mimicking portfolios on PC1 and PC2, constructed from the 10 assets. Mkt, SMB, and HML are the market, size and value factors of the Fama-French three-factor model. Each factor's position is given by its sample Sharpe ratio. The sample is quarterly from 1969Q1 to 2014Q4.

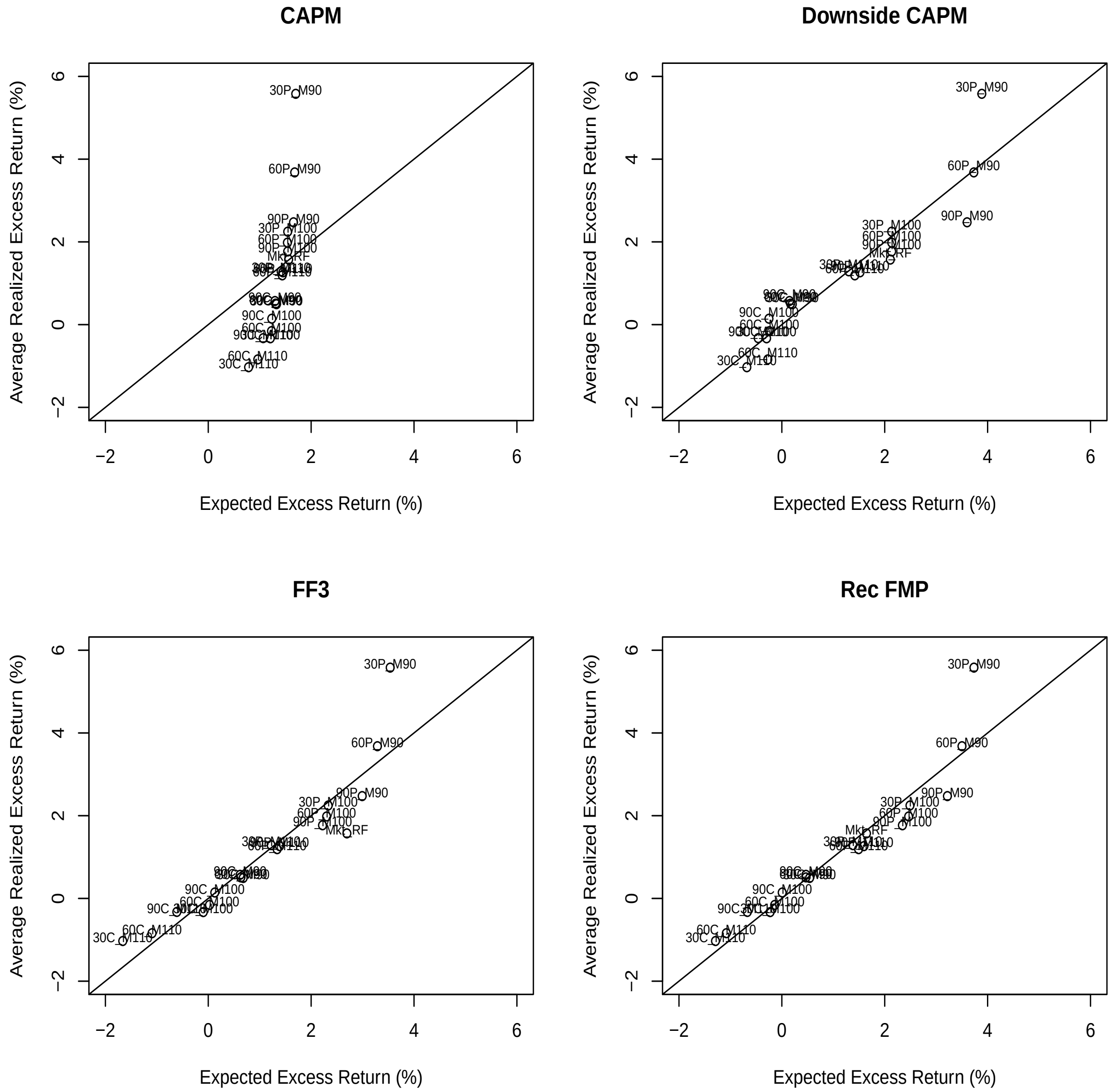

Figure 7: **Pricing Monthly Excess Returns on the SPX Index Options Portfolios, 4/1986-1/2012, 310 Months**

Figure 7 plots average realized excess returns on the 18 S&P 500 index option portfolios and the CRSP value-weighted index (labeled Mkt_rf) against the model-implied average excess returns. Each option portfolio is labeled in a way that the first two digits refer to maturity, C or P stand for call or put, respectively, and the last two digits denote moneyness. Each pricing model is estimated by a cross-sectional regression $E_T[R_t^e] = \beta'_{fac}\lambda_{fac} + \xi$ where $E_T[R_t^e]$ is the vector of average realized excess returns, and ξ is the vector of pricing errors. The model-implied average excess returns are $\beta'_{fac}\lambda_{fac}$. CAPM is the Capital Asset Pricing Model, DCAPM is the downside risk CAPM, FF3 denotes the Fama-French three-factor model, and Rec FMP are the factor mimicking portfolios of the recession risk model (See Table XIII for the factor mimicking portfolios.). The sample is monthly from 4/1986 to 1/2012, but returns are expressed in percentage terms per quarter.

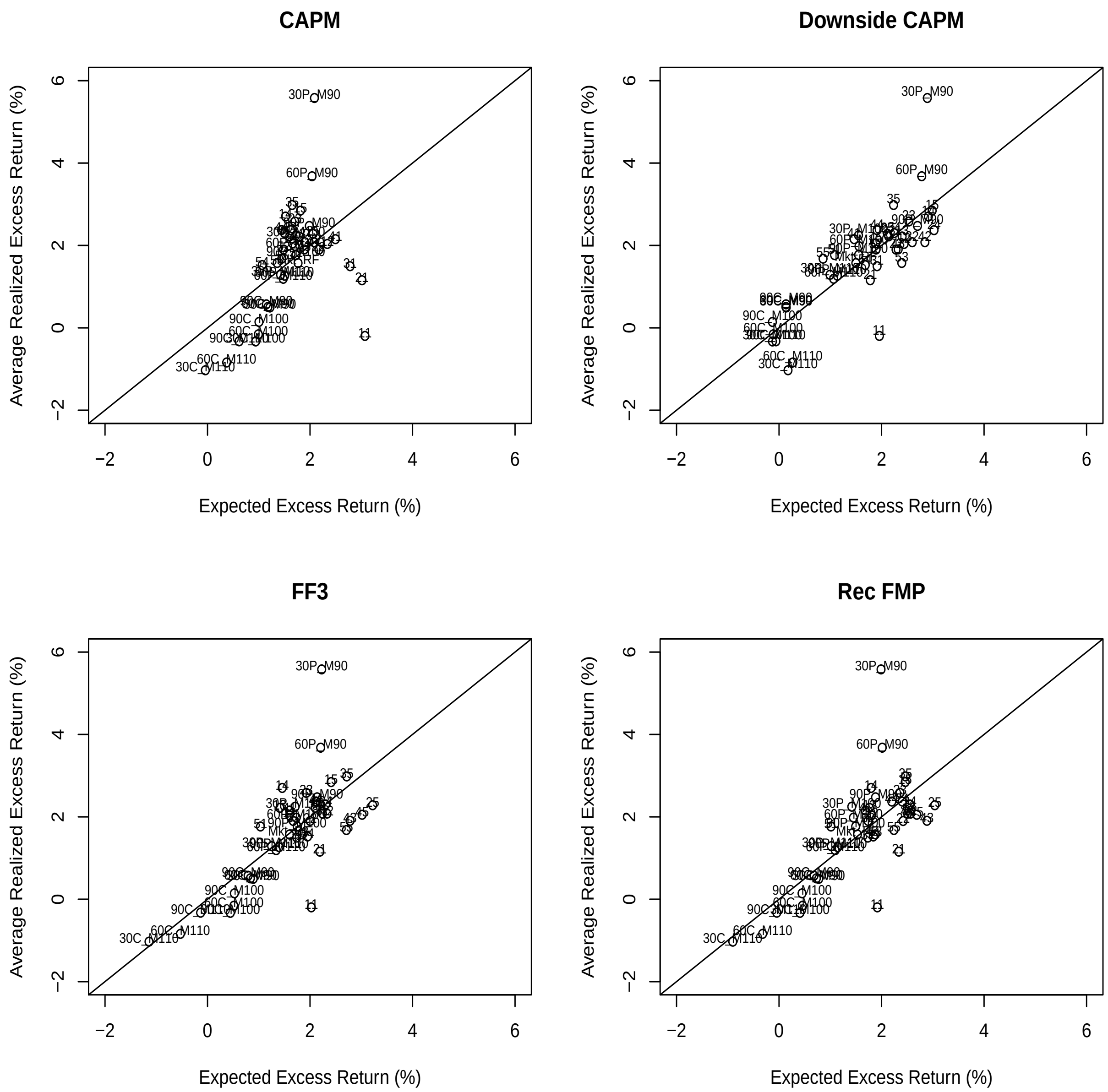

Figure 8: **Pricing Monthly Excess Returns on the SPX Index Options and the Fama-French 25 Size- and Book-to-Market-sorted Portfolios, 4/1986-1/2012, 310 Months**

Figure 8 plots average realized excess returns on the 18 S&P 500 Index option portfolios, the 25 Fama-French size- and book-to-market-sorted portfolios (labeled 11-55) and the CRSP value-weighted index (labeled Mkt_rf) against the mean excess returns predicted by four models. Each option portfolio is labeled in a way that the first two digits refer to maturity, C or P stand for call or put, and the last two digits denote moneyness. Each model is estimated by a cross-sectional regression $E_T[R_t^e] = \alpha\mathbf{1} + \beta'_{fac}\lambda_{fac} + \xi$ where $E_T[R_t^e]$ is the vector of the average excess returns, α is the excess zero-beta rate, and ξ is the vector of pricing errors. The predicted mean excess returns are $\alpha\mathbf{1} + \beta'_{fac}\lambda_{fac}$. CAPM is the Capital Asset Pricing Model, DCAPM is the downside risk CAPM, FF3 denotes the Fama-French three-factor model, and Rec FMP are the factor mimicking portfolios of the recession risk model (See Table XIII for the factor mimicking portfolios.). The sample is monthly from 4/1986 to 1/2012, but returns are expressed in percentage terms per quarter.

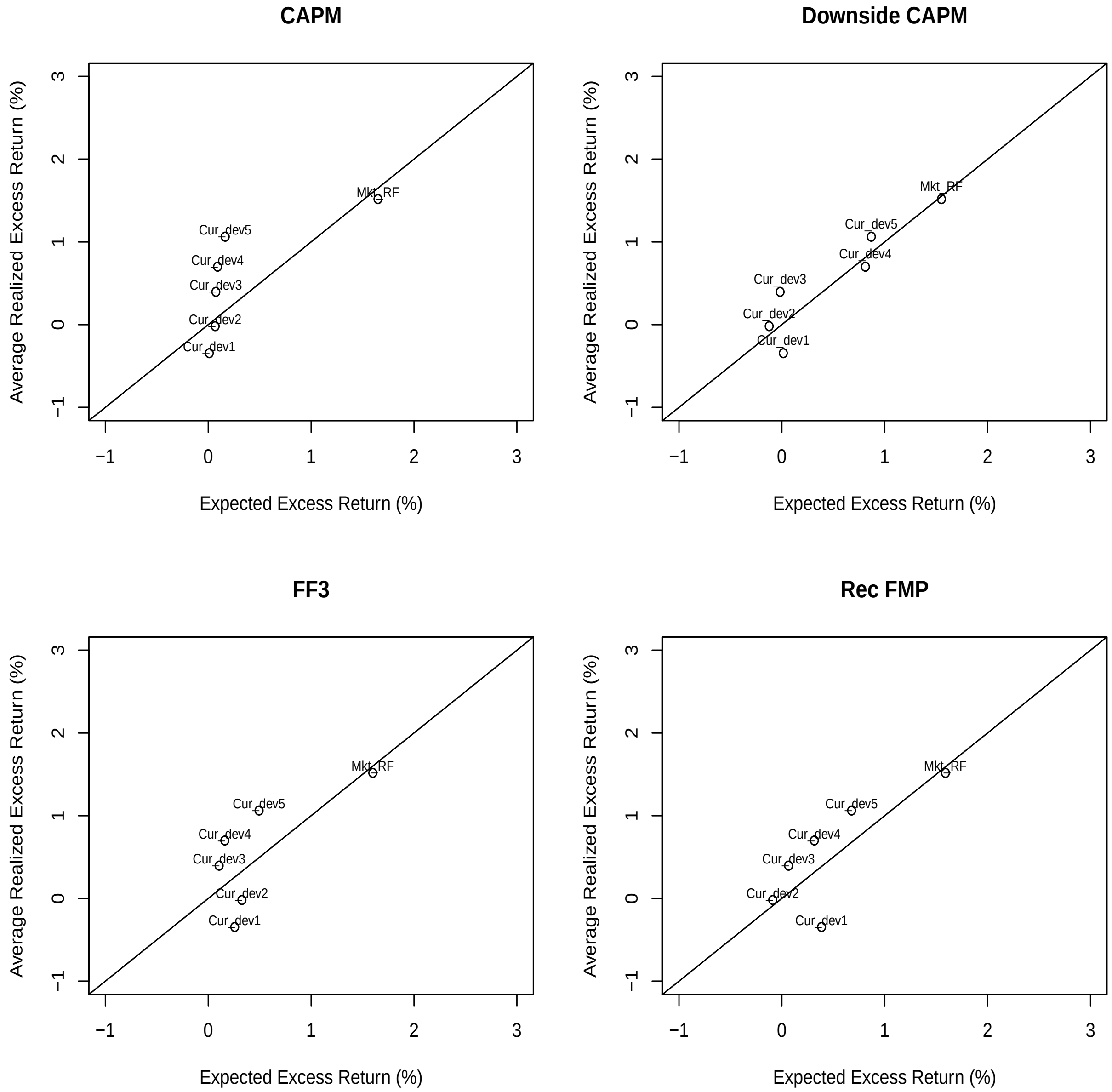

Figure 9: **Pricing Monthly Excess Returns on the Developed Countries' Currency Portfolios, 1/1974-3/2010, 435 Months**

Figure 9 plots the average realized excess returns on the 5 portfolios of currencies of developed countries sorted on nominal interest rates (labeled Cur_dev1-Cur_dev5) and the CRSP value-weighted index (labeled Mkt_rf) against the mean excess returns predicted by four models. Each model is estimated by a cross-sectional regression $E_T[R^e_t] = \beta'_{fac}\lambda_{fac} + \xi$ where $E_T[R^e_t]$ is the vector of the average excess returns, and ξ is the vector of pricing errors. The predicted mean excess returns are $\beta'_{fac}\lambda_{fac}$. CAPM is the Capital Asset Pricing Model, DCAPM is the downside risk CAPM, FF3 denotes the Fama-French three-factor model, and Rec FMP are the factor mimicking portfolios of the recession risk model (See Table XIII for the factor mimicking portfolios.). The sample is monthly from 1/1974 to 3/2010, but returns are expressed in percentage terms per quarter.

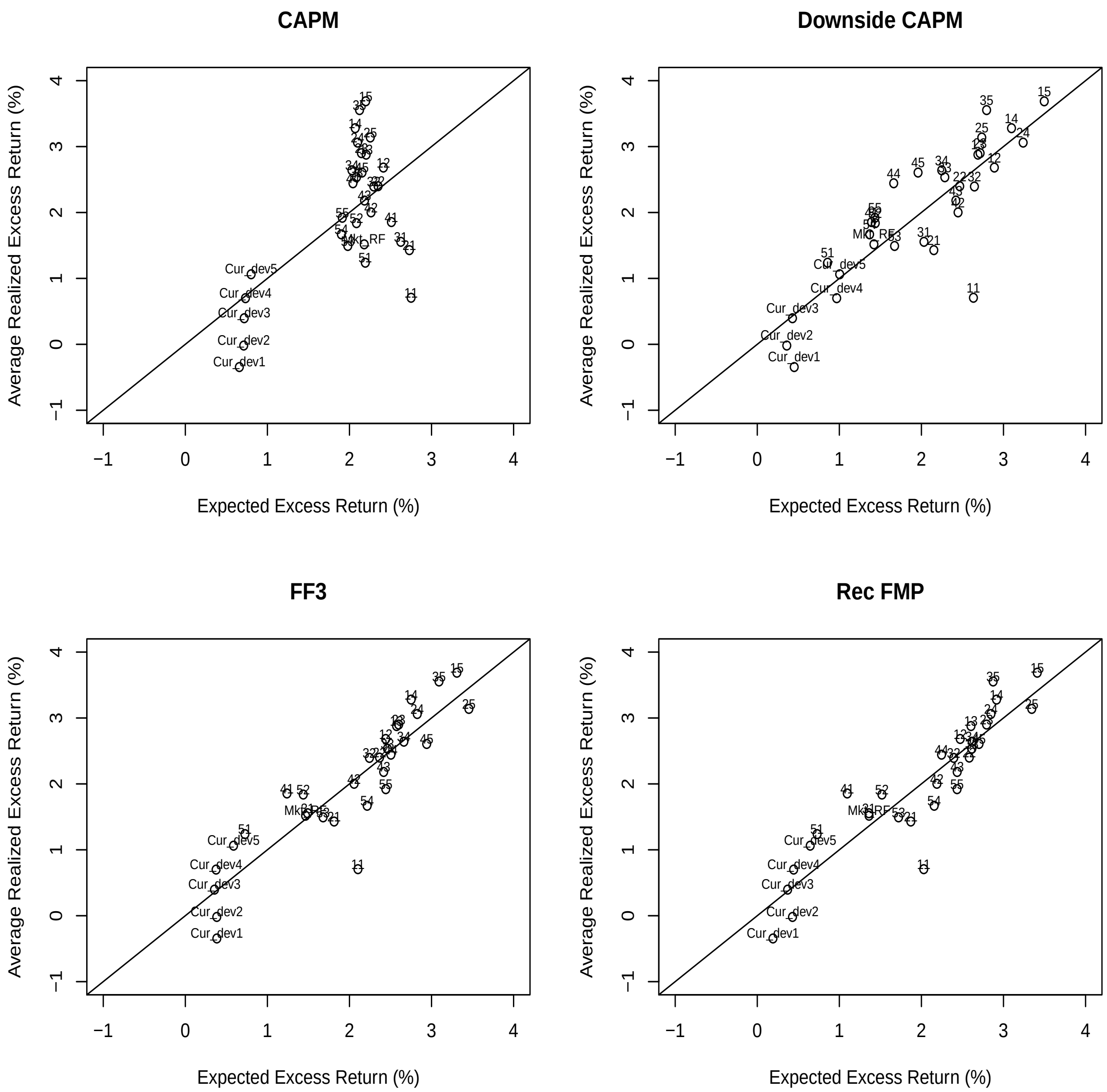

Figure 10: **Pricing Monthly Excess Returns on the Developed Countries' Currency and the Fama-French 25 Size- and Book-to-market-sorted Portfolios, 1974-2010**

Figure 10 plots average realized excess returns on the 5 portfolios of currencies of developed countries sorted on nominal interest rates (labeled Cur_dev1-Cur_dev5), the 25 Fama-French size- and book-to-market-sorted portfolios (labeled 11-55), and the CRSP value-weighted index (labeled Mkt_rf) against the average excess returns predicted by four models. Each model is estimated by a cross-sectional regression $E_T[R_t^e] = \alpha\mathbf{1} + \beta'_{fac}\lambda_{fac} + \xi$ where $E_T[R_t^e]$ is the vector of the average excess returns, α is the excess zero-beta rate, and ξ is the vector of pricing errors. The predicted mean excess returns are $\alpha\mathbf{1} + \beta'_{fac}\lambda_{fac}$. CAPM is the Capital Asset Pricing Model, DCAPM is the downside risk CAPM, FF3 denotes the Fama-French three-factor model, and Rec FMP are the factor mimicking portfolios of the recession risk model (See Table XIII for the factor mimicking portfolios.). The sample is monthly from 1/1974 to 3/2010, but returns are expressed in percentage terms per quarter.

Appendices

A Variable Definitions

- **Industrial production**: Seasonally adjusted industrial production index (INDPRO). Data source: Federal Reserve Economic Data (FRED).
- **Real GDP**: Quarterly seasonally adjusted final revised real GDP (GDPC1) in billions of chained 2009 dollars. Data source: FRED.
- **Real per capita consumption**: Aggregate consumption is measured by the sum of personal consumption expenditures on nondurable goods and services. Quarterly seasonally adjusted nominal personal consumption expenditures on nondurable goods and services are taken from the National Income and Product Accounts (NIPA) Table 2.3.5. These nominal consumption expenditures are deflated by their associated price indices from the NIPA Table 2.3.4 and are divided by the total population from the NIPA Table 2.1 to derive real per capita consumption. Data source: NIPA.
- **Real per capita labor income**: Following Jagannathan and Wang (1996), the nominal aggregate labor income is measured as the difference between the total personal income and the income from dividend. The real per capita labor income is the nominal aggregate labor income divided by total population and deflated by the Consumer Price Index (CPI) from Bureau of Labor Statistics (BLS). Data source: NIPA, BLS.
- **Default spread**: Spread between Moody's BAA and AAA corporate bond yields. Data source: FRED.
- **Term spread**: Spread between 10- and 1-year constant maturity Treasury yields. Data source: FRED.
- **CRSP dividend-price ratio**: CRSP monthly nominal dividends are derived from the difference between cum-dividend and ex-dividend monthly returns on the CRSP value-weighted index, multiplied by the previous month's ex-dividend CRSP index (Fama and French, 1988). The nominal dividends are deflated into real dividends by the CPI. The log dividend-price ratio is the logarithm of the annualized real dividends, formed as the past twelve month trailing sum of real dividends, divided by the current ex-dividend real CRSP index. The ex-dividend real CRSP index is the ex-dividend CRSP index deflated by the CPI. Data source: CRSP, BLS.
- **Short-term nominal interest rate**: Three-month T-Bill rate (secondary market rate). Data source: FRED.